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Intellectual Property and Regional Growth in Türkiye: A Spatial Analysis of Education, Trade, and Population Dynamics

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Abstract

This research investigates the determinants of regional economic growth in Türkiye between 2008 and 2023, focusing on GDP persistence, population density, trade openness, education, and intellectual property rights (IPRs), particularly patent, utility model, trademark, and industrial design registrations. Spatial panel data analysis with spatial autoregressive model (SAR), spatial durbin model (SDM), and spatial error model (SEM) is applied to 81 cities at the NUTS-III level, providing a comprehensive perspective on regional dynamics. The findings confirm statistically significant spatial autocorrelation, indicating that neighboring cities influence each other's economic performance. GDP persistence and population density positively affect growth, while tertiary education negatively correlates with GDP. Trade openness is not statistically significant. Design and utility model registrations contribute positively to growth, whereas patents and trademarks show negative effects, highlighting the need for policy alignment with regional economic structures.

Keywords Intellectual Property Rights · Regional Economic Growth · Education and Human Capital · Spatial Panel Data Analysis · Trade Openness

JEL Classification O34 · O47 · I23

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Intellectual Property and Regional Growth in Türkiye: A Spatial Analysis of Education, Trade, and Population Dynamics

Intellectual property rights (IPRs) are a key policy tool for fostering innovation, attracting investment, and enhancing industrial competitiveness in today's knowledge-driven global economy. Patents, utility models, industrial designs, and trademarks incentivize firms and individuals to engage in research and development by providing legal protection for intellectual assets. However, the role of IPRs in economic development remains debated, as excessive protection can hinder competition, limit knowledge spillovers, and create monopolistic market structures.

A patent grants exclusive rights to an inventor for a novel, inventive, and industrially applicable innovation, typically for 20 years (Encaoua et al., 2006). Global patent systems are governed by the TRIPS Agreement and facilitated by the Patent Cooperation Treaty (PCT) (Maskus, 2019). In Türkiye, patents are regulated under Industrial Property Law No. 6769 (2017), aligning with the European Patent Convention and the TRIPS Agreement. Utility models, a more accessible form of patent protection, cover incremental innovations and technical improvements with lower novelty requirements and a shorter protection period (6-10 years, varying by country) (Suthersanen, 2006). Countries such as China, Japan, and South Korea use utility models to support local companies and SMEs (Prud'homme, 2017). In Türkiye, they are granted without substantive examination and provide a 10-year protection period (Industrial Property Law No. 6769, 2017).

Industrial design rights safeguard a product's functionality and visual aspects, including shape, symbolism, and texture (Yoshioka-Kobayashi et al., 2018). Internationally regulated by the Hague Agreement on Industrial Designs (Suluk, 2012), their protection period ranges from 5 to 25 years in the EU (Monseau, 2011). In Türkiye, Industrial Property Law No. 6769 (2017) provides an initial five-year protection, which is renewable for up to 25 years. Trademarks protect distinctive signs, logos, names, or symbols, ensuring brand identity and consumer recognition (Devarhubli, 2022). Governed by the Madrid Agreement Protocol, trademarks registered through WIPO receive a 10-year renewable protection (Preoteasa et al., 2017). Türkiye's trademark system follows similar principles, granting 10-year renewable protection (Industrial Property Law No. 6769, 2017).

While Türkiye has aligned its patent system with European and international standards, it continues its efforts to integrate into global innovation networks (Onuklu et al., 2021). Recent reforms under Industrial Property Law No. 6769 (2017) aim to enhance R&D investments through tax incentives, increase international patent filings, and strengthen technology transfer mechanisms. While patents remain essential for high-tech industries, utility models serve as a cost-effective innovation protection tool for the private sector. However, the less stringent examination process for utility models raises concerns about the risk of low-quality registrations. The key differences in the scope, duration, and benefits of these IPRs according to Turkish law are summarized in Table 1.

Industrial designs have gained prominence in Türkiye, particularly after 2002, as the manufacturing sector expanded in production and capacity utilization (Hasdoğan, 2009). Similarly, trademarks became crucial after 1995, following Türkiye's commitments to the WTO, TRIPS, and the EU-Turkey Customs Union (Suluk, 2012).

Table 1
Differences and Common Points of IPRs

IPR	Scope of Protection	Duration (Industrial Property Law No. 6769, 2017)	Key Benefits
Patent	Novel, industrially applicable inventions	20 years (no renewal) (Art. 101)	Encourages high-level innovation
Utility model	Small technical improvements (novelty requirement differs from patents)	10 years (no renewal) (Art. 101)	Supports SMEs; faster approval process
Industrial design	Visual/aesthetic features of products	5–25 years (renewable in 5-year periods up to 25 years) (Art. 69)	Protects product appearance; supports branding
Trademark	Distinctive brand identifiers (names, visuals, etc.)	10 years (renewable in 10-year periods) (Art. 23)	Ensures brand recognition; helps prevent counterfeiting

Source: Summarized by the Author based on the Industrial Property Law No. 6769 (2017) and the abovementioned literature.

However, some scholars argue that excessive trademark registrations may restrict market competition and create entry barriers, granting monopolistic advantages to dominant firms (Schautschick & Greenhalgh, 2016). Thus, balancing innovation incentives with competitive market dynamics remains a key policy challenge.

In advanced economies, strong IPR frameworks encourage R&D investments, enabling firms to gain competitive advantages through innovation. These protections particularly benefit high-value industries, such as pharmaceuticals, technology, and engineering, fostering long-term economic growth. Conversely, in developing economies, IPR impacts are more complex. While patents and trademarks attract foreign investment and technology transfer, they may also restrict domestic firms' ability to build on existing innovations. As a result, many developing economies rely on flexible IPR mechanisms, such as utility models and industrial designs, to foster local innovation and gradual technological advancement. Bulus and Bakirtas (2021) highlight that IPR protection's economic impact varies by development level, with patents benefiting developed economies, whereas utility models contribute more positively to growth in developing countries.

The key challenge is ensuring that IPR policies protect intellectual assets without creating barriers to knowledge diffusion and economic inclusivity. While the economic impacts of IPRs are widely studied at the national level, a significant gap remains in understanding these dynamics at a subnational scale. This omission is particularly pronounced in the context of Türkiye, an emerging economy with significant regional disparities, where most prior research has national aggregates without accounting for the complex spatial interdependencies and spillover effects between neighboring provinces. Overlooking these geographical dynamics provides an incomplete picture of the factors driving regional growth.

To address these limitations, this study's primary objective is to provide a comprehensive regional analysis of the spatially dependent impact of various IPRs, namely patents, utility models, trademarks, and industrial designs, on economic performance across Türkiye's provinces. Using a panel dataset for 81 provinces (NUTS-III) from 2008 to 2023, this research employs a suite of static and dynamic spatial panel data models (SAR, SDM, and SEM). This approach allows the study to explicitly quantify the crucial intercity spillover effects, thereby offering a more granular and nuanced perspective on the drivers of regional growth than has been previously available in the literature on Türkiye.

Literature Review

Impacts of Intellectual Property Rights

IPRs are critical for economic growth, incentivizing innovation by protecting intellectual assets. The four major IPRs—patents, utility models, industrial designs, and trademarks—have distinct economic impacts depending on their design and market context. While patents and trademarks can create monopolistic behavior, utility models and designs are argued to facilitate broader innovation access, especially in developing economies (Prud'homme, 2017; Suthersanen, 2006).

Strong IPR protection is shown to enhance technology transfer, attracts FDI, and drives growth (Dinopoulos & Segerstrom, 2010), with TRIPS-era reforms boosting exports and knowledge spillovers (Ivus, 2010). Reinforcing this perspective, recent studies show that patents and trademarks are important for FDI and global market integration (Shaikh et al., 2024) and for promoting key sectors like renewable energy adoption (Khan et al., 2024). However, this positive effect may be non-linear and subject to a threshold beyond which excessive protection suppresses competition (Ramos et al., 2024). Furthermore, overly strict patent regimes can hinder competition, create patent thickets that lead to costly litigation (Encaoua et al., 2006; Kwan and Lai, 2003), slow cumulative innovation, and limit technology diffusion, particularly in developing economies (Moser, 2013; Maskus, 2019).

In contrast, other IPRs are often viewed as more accessible innovation tools. Utility models, which offer protection for incremental innovations, benefit SMEs and support technological catch-up in industrializing economies like China, Japan, and South Korea (Suthersanen, 2006; Prud'homme, 2017). Similarly, industrial design rights enhance sectoral competitiveness and market value (Bielig, 2015; Yoshioka-Kobayashi et al., 2018), linking to faster revenue growth (Schartinger, 2023) and more inclusive innovation (Heikkilä, 2019).

Trademarks play a dual role; they are vital for brand identity but can enable market dominance without necessarily fostering innovation (Schautschick & Greenhalgh, 2016). They may create market entry barriers (Beebe & Fromer, 2017) and play a lesser role than patents in attracting R&D-based FDI (Park and Lippoldt, 2008). Their effect may also vary over time, with high initial branding costs negatively affecting short-term growth but contributing positively in the long run (Ökten et al., 2019).

Ultimately, the effectiveness of IPRs varies significantly with the level of economic development. Patents are often more impactful in developed economies, whereas utility models better support technological catch-up in developing economies (Kim et al., 2012). This divergence is evident in contrasting country-specific findings, such as a negative effect of utility models in Germany (Bielig, 2015) versus no significant IPR-growth link in Nigeria (Ezenwakwelu et al., 2024).

Empirical Literature on Türkiye

Empirical studies on Türkiye reveal a complex and often ambiguous relationship between IPRs, innovation, and economic growth. A consistent theme is the positive impact of R&D expenditures on the economy (Gülmez & Akpolat, 2014; Köse & Şentürk, 2017). In contrast, the direct role of patents is highly contested. Findings on patents range from positive for growth and exports (Işık, 2014; Sungur et al., 2016; Dereli, 2019), to insignificant (Köse & Şentürk, 2017), negative in the manufacturing sector (Bayarçelik & Taşel, 2012), or that both patents and utility models are insignificant for firm performance (Bulus & Bakırtaş, 2021). Several studies also confirm a positive long-term IPR-growth link in broader OECD contexts that include Türkiye (Özcan & Özer, 2017; Dağlı & Ezanoğlu, 2021).

Research on other IPRs also shows mixed results. While some studies find positive effects of industrial designs on sales and exports (Bidirici & Bohur, 2015; Durmuşkaya & Ersoy, 2016) and a causal link from all major IPRs to GDP (Duman, 2017), others report that trademarks are statistically insignificant for Türkiye's growth (Bozkaya et al., 2020). The complexity is further highlighted by findings that an innovation index can have a negative immediate impact but a positive lagged effect on GDP (Yıldız, 2018).

The existing literature suffers from several limitations. It predominantly focuses on patents, often using applications instead of the more accurate measure of registrations, and gives limited attention to utility models, designs, and trademarks. Crucially, while national-level effects are debated, recent analysis reveals significant regional disparities and an uneven concentration of patents in Türkiye (Abay et al., 2021). This suggests that prior studies, by overlooking geographical dynamics, may miss critical spillover effects. The importance of such a regional approach is underscored by recent subnational studies on China. Research at the county and university levels confirms that IP-related policies and innovation activities generate significant positive spatial spillovers, affecting the economic growth and patenting behavior of neighboring counties and institutions (Gu, 2023; Yu & Shen, 2024). This international precedent strengthens the case for applying a spatial econometric approach to the Turkish context.

This study addresses these key gaps. First, it incorporates a broader range of IPRs—utility models, design registrations, and trademarks—for a more comprehensive analysis. Second, unlike prior studies, it employs spatial econometric methods to explicitly capture intercity innovation diffusion. Finally, it enhances methodological rigor through Bayesian model selection to ensure robust specifications. By revealing the heterogeneous effects of IPRs, this study challenges the assumption of uniform impacts, highlighting how different IPR types influence performance based on regional dynamics. This nuanced perspective is essential for designing targeted, innovation-driven growth policies.

Theoretical Framework

Schumpeterian Growth Theory posits that innovation and "creative destruction" drive long-term economic growth (Schumpeter, 1934, 1942). This concept, formalized into an endogenous growth model by Aghion and Howitt (1992), was later expanded to include firm-level productivity (Aghion et al., 2015), skill gaps between nations (Acemoglu and Zilibotti, 2001), and the impact of artificial intelligence and automation (Aghion et al., 2019). Within this framework, IPRs are crucial for incentivizing R&D investment. However, excessive protection may create monopolies and slow knowledge diffusion, thereby stifling the very creative destruction process it is meant to encourage.

Examining the competitive implications of IPR-driven innovation, Market Power Theory, originating with Cournot (1838), suggests that firms with market dominance can set prices above competitive levels, reducing consumer welfare. The theory evolved with Marshall's (1890) work on demand elasticity, followed by concepts of imperfect and monopolistic competition (Chamberlin, 1933; Robinson, 1933), structural entry barriers (Bain, 1956), oligopolistic collusion (Stigler, 1964), and contestable markets (Baumol, 1982), with modern analyses using game theory to examine digital markets (Tirole, 1988; Motta, 2004). From this perspective, IPRs can grant firms monopolistic positions that enable reinvestment in R&D and fuel further innovation. However, such market power can also reduce competition, limit technology access, and lead to rent-seeking behavior instead of innovation, ultimately harming growth.

Addressing the broader societal impact of protected knowledge, the Innovation Spillover Hypothesis argues that knowledge diffuses beyond its creator, generating external economic benefits (Marshall, 1890; Arrow, 1962). Empirical work has demonstrated these spillovers in R&D (Griliches, 1979) and their dependence on geographic proximity (Jaffe, 1986), a firm's market position in the technology and product market (Bloom et al., 2013), and demand-side factors (Acemoglu and Linn, 2004). This theory highlights the central tension for IPR policy: balancing the need to incentivize private innovation with the public good of widespread knowledge dissemination. Overly strict IPRs can limit these crucial spillovers, whereas a well-balanced framework can foster both invention and diffusion, maximizing cumulative economic growth.

Endogenous Growth Model and Econometric Approach

The endogenous growth model, introduced by Romer (1986), emphasizes the importance of human capital, innovation, knowledge spillovers economic growth in the long run, challenging the exogenous assumptions of Solow's (1956) growth model. Romer (1990) extended this framework by highlighting the role of R&D and technological change in sustaining growth. Subsequent research, including Jones (1995), refined the model by incorporating scale effects and policy implications. Recent advancements explore the role of automation and artificial intelligence in endogenous growth (Acemoglu & Restrepo, 2018).

Data and Econometric Model

Romer (1990) updated his original AK model by explicitly incorporating human capital in Romer (1986), which can be formulized as:

$$Y_t = A_t K_t^{\alpha} H_t^{\beta} L_t^{1-\alpha-\beta} \tag{1}$$

In this extended model:

Y_t = Output (GDP) at time t

A_t = Technological progress (driven by IPRs)

K_t = Capital (represented by trade openness and past GDP)

H_t = Human capital (proxied by the ratio of tertiary graduates in the population)

L_t = Labor force (proxied by population density)

Technological Progress (A_t) from IPRs

$$A_t = (PAT_t)^{\theta}(UM_t)^{\phi}(TM_t)^{\eta}(ID_t)^{\kappa} \tag{2}$$

PAT_t = Patents, UM_t = Utility models, TM_t = Trademarks, ID_t = Industrial designs

Capital (K_t)

$$K_t = (TO_t)^{\gamma}(Y_{t-1})^{\lambda} \tag{3}$$

TO_t = Trade openness (investment and market expansion)

Y_{t-1} = Lagged GDP (path dependence and past accumulation)

Human Capital (H_t)

$$H_t = (GRAD_t)^{\delta} \tag{4}$$

$GRAD_t$ = Ratio of tertiary graduates in the population

Labor Force (L_t)

$$L_t = (POP_t)^{\rho} \tag{5}$$

POP_t = Population density

GDP – Natural Logarithm of Gross Domestic Product (based on 2009) in USD, TO – Trade Openness (Trade/GDP), and GRAD (number of people with a tertiary degree, including master's and PhD graduates, as a share of the respective city's population) are obtained from TurkStat (2024). POP (population per km²) is sourced from both TurkStat (2024) and the Republic of Türkiye Ministry of National Defence (2024) and is calculated by the author. PAT, UM, TM, and ID represent the number of patents, utility models, trademarks, and industrial designs, respectively, and are obtained from the Turkish Patent Institute (2024). Additionally, the tertiary graduate and population data were obtained from TurkStat (2024) and transformed using the natural logarithm to create the variables log_tertiary and log_pop. These variables were then used in the correlation analysis. Since data on education are available since 2008, the analysis covers 81 provinces at the NUTS-III level for the period 2008-2023.

IPRs drive technological progress (A_t), influencing productivity across all sectors.
Capital (K_t) consists of trade openness and past GDP, reflecting external market integration and historical accumulation.

Human capital (H_t) is represented by tertiary graduates, enhancing innovation and skilled labor contributions.
(L_t) is represented by population density, capturing workforce size and potential spillover effects.

$$Y_t = [(PAT_t)^{\theta}(UM_t)^{\phi}(TM_t)^{\eta}(ID_t)^{\kappa}] \times [(TO_t)^{\gamma}(Y_{t-1})^{\lambda}]^{\alpha} \times (GRAD_t)^{\beta} \times (POP_t)^{1-\alpha-\beta} \tag{6}$$

In accordance with the theoretical model mentioned above, the following econometric model was created:

$$\begin{gathered} Y_{it} = \rho WY_{it} + \alpha_1 TO_{it} + \alpha_2 Y_{i,t-1} + \beta GRAD_{it} + \gamma POP_{it} + \delta_1 PAT_{it} + \delta_2 UM_{it} + \delta_3 TM_{it} + \\ \delta_4 ID_{it} + \nu_i + \lambda_t + \varepsilon_{it} \end{gathered} \tag{7}$$

Y_{it}= GDP of region i at time t (economic output)

WY_{it}= Spatially lagged GDP (captures spillover effects)

ρ = Spatial autoregressive coefficient

μ_i = Region-specific fixed effects

ν_i = Random effects (RE) term

λ_t = Time-specific effects

ε_{it} = Error term

α_1 = Effect of Trade Openness (TO_{it}), representing capital openness

α_2 = Effect of Lagged GDP ($Y_{i,t-1}$), capturing past economic performance

β = Effect of Tertiary Graduates ($GRAD_{it}$), proxy for human capital

γ = Effect of Population Density (POP_{it}), proxy for labor force availability

δ_1 = Effect of Patents (PAT_{it}), capturing high-tech innovation

δ_2 = Effect of Utility Models (UM_{it}), representing incremental innovations

δ_3 = Effect of Trademarks (TM_{it}), reflecting brand value and market differentiation

δ_4 = Effect of Industrial Designs (ID_{it}), capturing aesthetic and functional innovations

In order to ensure the robustness of the model results, 12 models, illustrated in Table 2, derived from the general model were estimated statically and dynamically with different estimators. Using multiple model specifications ensures that the core relationships between variables remain consistent across different formulations. If key coefficients remain stable across models, it strengthens the validity of the findings and reduces concerns about model dependency.

Dynamic models, which include lagged GDP ($GDP_{i,t-1}$), help address endogeneity concerns by accounting for economic persistence. These models ensure that past economic performance does not bias the estimated effects of other explanatory variables. IPRs, including patents, utility models, trademarks, and industrial designs tend to be highly correlated. To avoid biased estimates due to multicollinearity, each IPR variable is isolated in different models, providing a clearer understanding of their independent effects.

Variables like GDP may act as suppressor variables, indirectly influencing relationships in the model. Running multiple specifications helps identify such effects and ensures that the results are not distorted by omitted-variable bias. The combination of Spatial Autoregressive Model (SAR), the Spatial Durbin Model (SDM), and the Spatial Error Model (SEM) with both static and dynamic models allows for a more comprehensive analysis. This approach accounts for spatial dependence in GDP, spillover effects, and unobservable spatial shocks, providing a clearer distinction between short-term and long-term economic impacts.

Table 2

Econometric Model Specifications

Model	Eq.	
Model 1	$GDP_{i,t} = \alpha GDP_{i,t-1} + \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_4 PAT_{i,t} + \beta_5 UM_{i,t} + \beta_6 TM_{i,t} + \beta_7 ID_{i,t} + u_{it}$	(8)
Model 2	$GDP_{i,t} = \alpha GDP_{i,t-1} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_4 PAT_{i,t} + \beta_5 UM_{i,t} + \beta_6 TM_{i,t} + \beta_7 ID_{i,t} + u_{it}$	(9)
Model 3	$GDP_{i,t} = \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_4 PAT_{i,t} + \beta_5 UM_{i,t} + \beta_6 TM_{i,t} + \beta_7 ID_{i,t} + u_{it}$	(10)
Model 4	$GDP_{i,t} = \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_4 PAT_{i,t} + \beta_5 UM_{i,t} + \beta_6 TM_{i,t} + \beta_7 ID_{i,t} + u_{it}$	(11)
Model 5	$GDP_{i,t} = \alpha GDP_{i,t-1} + \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_7 ID_{i,t} + u_{it}$	(12)
Model 6	$GDP_{i,t} = \alpha GDP_{i,t-1} + \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_5 UM_{i,t} + u_{it}$	(13)
Model 7	$GDP_{i,t} = \alpha GDP_{i,t-1} + \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_6 TM_{i,t} + u_{it}$	(14)
Model 8	$GDP_{i,t} = \alpha GDP_{i,t-1} + \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_4 PAT_{i,t} + u_{it}$	(15)
Model 9	$GDP_{i,t} = \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_7 ID_{i,t} + u_{it}$	(16)
Model 10	$GDP_{i,t} = \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_5 UM_{i,t} + u_{it}$	(17)
Model 11	$GDP_{i,t} = \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_6 TM_{i,t} + u_{it}$	(18)
Model 12	$GDP_{i,t} = \beta_1 POP_{i,t} + \beta_2 GRAD_{i,t} + \beta_3 TO_{i,t} + \beta_4 PAT_{i,t} + u_{it}$	(19)

Methodology

This study employs a spatial econometric framework to analyze the impact of IPRs on regional economic growth in Türkiye. Both static and dynamic spatial panel models are estimated using the Maximum Likelihood (ML) estimator, which is well-suited for spatial dependence and remains robust in dynamic settings. The models considered include the SAR, SDM and the SEM, along with the Lee-Yu transformation to control for unobserved heterogeneity. To determine the most appropriate econometric specification, Bayesian Model Comparison using log marginal likelihoods suggested by LeSage (2014) is applied. Additionally, spatial impact analysis is conducted for SAR and SDM models to decompose direct, indirect, and total effects.

This study accounts for spatial dependence by utilizing a row-standardized spatial weights matrix constructed using the queen contiguity criterion. Under this criterion, a region is considered a neighbor if it shares either a boundary or a vertex with another region, ensuring a more inclusive definition of spatial interaction. The spatial weights matrix (W) plays a crucial role in distinguishing spatial panel models from standard panel models, as it captures interregional dependencies. The matrix is defined as follows:

$$w_{ij} = \begin{cases} 1 \text{ if regions i and j share a boundary or vertex} \\ 0 \text{ otherwise} \end{cases} \tag{20}$$

To maintain consistency in spatial effect interpretation and facilitate comparability, the weights matrix is row-standardized. This transformation ensures that the sum of weights for each region equals 1, thereby mitigating scale-related distortions and improving the robustness of spatial econometric estimations.

Spatial Panel Data Estimation Techniques

The SAR model, introduced by Cliff and Ord (1973, 1981) and further developed by Anselin (1988), accounts for spatial dependence by including a lagged version of the dependent variable from neighboring regions. The general form of the SAR model is:

$$y = \rho Wy + X\beta + \varepsilon \tag{21}$$

where:

y is the dependent variable,

W is the spatial weight matrix,

ρ is the spatial autoregressive coefficient capturing spillover effects,

X is the matrix of explanatory variables,

β is the vector of coefficients,

$\varepsilon \sim N(0, \sigma^2 I)$ is the error term.

A positive and significant ρ indicates that the economic performance of a region is influenced by the performance of its neighboring regions. The SAR model assumes that spatial dependence primarily arises through the dependent variable.

Building on SAR, the SDM, proposed by LeSage and Pace (2009), extends the spatial dependence structure by including spatially lagged explanatory variables. The SDM is given by

$$y = \rho Wy + X\beta + WX\theta + \varepsilon \tag{22}$$

Where $WX\theta$ represents the spatially lagged independent variables, capturing the influence of explanatory variables from neighboring regions on the dependent variable. The SDM is particularly useful in detecting indirect (spillover) effects, as it allows for a richer spatial structure compared to SAR. If the restriction $\theta = 0$ holds, the SDM reduces to the SAR model.

The SEM, formulated by Anselin (1988), assumes that spatial dependence occurs through the error term rather than the dependent or independent variables. The model is specified as

$$y = X\beta + u \tag{23}$$

$$u = \lambda Wu + \varepsilon \tag{24}$$

where:

u is the spatially autocorrelated error term, λ captures spatial dependence in the errors.

The SEM accounts for omitted spatially correlated variables and corrects for spatial autocorrelation in the residuals. If λ is significant, ignoring spatial dependence could lead to biased and inefficient estimations.

Yu et al. (2008) explored estimation techniques in spatial panel models, highlighting the challenges associated with fixed effects (FE) and the need for bias correction. Building on this, Lee and Yu (2010a, 2010b) proposed a transformation that corrects for bias in spatial panel models with fixed effects. This transformation is particularly useful in dynamic settings, where conventional fixed-effects estimators may produce inconsistent estimates. By eliminating the incidental parameter problem, the Lee-Yu transformation improves the efficiency of spatial panel estimates.

To determine the most appropriate econometric specification, Bayesian Model Comparison based on log marginal likelihoods is applied. This approach evaluates the relative performance of different models by balancing goodness-of-fit and model complexity. A higher log-marginal value indicates a better model fit, allowing for a data-driven selection of the most efficient estimator (LeSage, 2014).

For SAR and SDM models, the estimated coefficients do not directly reflect the full impact of explanatory variables due to feedback loops in the spatial structure. The spatial impact decomposition method by LeSage and Pace (2009) distinguishes between the direct effects of a variable within a region and the indirect spillover effects on neighboring regions, which together constitute the total effect. This decomposition is important in SDM models, where both the dependent and independent variables exhibit spatial dependence. The impact analysis provides a clearer interpretation of spatial interdependencies in the estimated models.

The inclusion of dynamic spatial models incorporates temporal dependencies by introducing the lagged dependent variable, resulting in a dynamic spatial autoregressive or dynamic SDM specification:

$$y_t = \rho W y_t + \phi y_{t-1} + X_t \beta + W X_t \theta + \varepsilon_t \tag{25}$$

where ϕ captures the persistence of the dependent variable over time. The ML estimator, used throughout this study, is particularly robust in dynamic spatial settings. By integrating these spatial econometric techniques, this research provides a comprehensive analysis of IPRs in regional economic development, addressing both spatial and temporal interdependencies in economic growth dynamics.

Findings and Discussions

Preliminary and Diagnostic Tests

Efforts were made to transform the data into the most suitable form to prevent correlation among variables from biasing the estimates following the construction of the models. As part of this process, the correlation matrix, which is illustrated in Table 3, was examined. The log_pop and log_tertiary variables were highly correlated with each other and with GDP(t-1), necessitating their transformation. To address this, log_pop was replaced with POP, which represents population density (measured as population per km²), while log_tertiary was replaced with the ratio of tertiary graduates to the total population. These adjustments helped reduce high correlation values.

Table 3

Correlation Matrix

Variable	GDP	GDP (t-1)	POP	log_pop	GRAD	log_tertiary	TO	ID (t-1)	UM (t-1)	TM (t-1)	PAT (t-1)
GDP	1.000	0.994	0.594	0.948	0.290	0.910	0.532	0.583	0.584	0.535	0.496
GDP(t-1)	0.994	1.000	0.594	0.948	0.289	0.913	0.528	0.583	0.583	0.534	0.495
POP	0.594	0.594	1.000	0.530	0.211	0.524	0.508	0.551	0.520	0.553	0.589
log_pop	0.948	0.948	0.530	1.000	0.179	0.900	0.498	0.541	0.531	0.496	0.455
GRAD	0.290	0.289	0.211	0.179	1.000	0.570	0.228	0.203	0.180	0.245	0.267
log_tertiary	0.910	0.913	0.524	0.900	0.570	1.000	0.510	0.526	0.512	0.499	0.470
TO	0.532	0.528	0.508	0.498	0.228	0.510	1.000	0.476	0.400	0.408	0.397
ID(t-1)	0.583	0.583	0.551	0.541	0.203	0.526	0.476	1.000	0.919	0.923	0.842
UM(t-1)	0.584	0.583	0.520	0.531	0.180	0.512	0.400	0.919	1.000	0.845	0.719
TM(t-1)	0.535	0.534	0.553	0.496	0.245	0.499	0.408	0.923	0.845	1.000	0.950
PAT(t-1)	0.496	0.495	0.589	0.455	0.267	0.470	0.397	0.842	0.719	0.950	1.000

Source: Own calculations.

Further examination of variable correlations revealed that GDP(t-1), POP, GRAD, and TO had correlation coefficients below 0.60 with other variables, suggesting no severe multicollinearity issues. However, IPR variables (patents, utility models, trademarks, and industrial designs) exhibited correlations above 0.70, indicating a high degree of interdependence. Including all IPR variables in a single model could lead to multicollinearity issues, potentially distorting the estimates. Additionally, the SPML and SDPDMOD packages in R, which were used for estimation, do not perform calculations in the presence of multicollinearity.

To mitigate these risks and ensure robustness, multiple models were estimated, allowing for comparison of results. Some models included all variables, while others examined IPR variables separately, isolating their effects. Given that the study focuses on the economic impact of IPRs, analyzing each variable individually was crucial. Therefore, rather than employing Principal Component Analysis (PCA) to aggregate these variables, they were examined separately to capture their distinct effects.

To detect temporal autocorrelation and heteroskedasticity in the models presented in Table 2, several diagnostic tests were conducted. Breusch-Pagan and Modified Wald tests were applied to assess heteroskedasticity, while Wooldridge and Durbin-Watson tests were used to detect autocorrelation. The results, summarized in Table 4, indicate the presence of temporal autocorrelation in all models, while heteroskedasticity was identified in models 3, 4, 9, 10, 11, and 12.

Table 4

Heteroskedasticity and Autocorrelation Tests

Model Name	Heteroskedasticity Tests		Autocorrelation Tests	
	Breusch-Pagan Test	Modified Wald Test	Wooldridge Test	Durbin-Watson Test
Model-1	No significant heteroskedasticity (0.118)	No significant heteroskedasticity (0.118)	Significant autocorrelation (0)	Significant autocorrelation (0.021)
Model-2	No significant heteroskedasticity (0.104)	No significant heteroskedasticity (0.104)	Significant autocorrelation (0)	Significant autocorrelation (0.021)
Model-3	Significant heteroskedasticity (0)	Significant heteroskedasticity (0)	Significant autocorrelation (0)	Significant autocorrelation (0)
Model-4	Significant heteroskedasticity (0)	Significant heteroskedasticity (0)	Significant autocorrelation (0)	Significant autocorrelation (0)
Model-5	No significant heteroskedasticity (0.089)	No significant heteroskedasticity (0.089)	Significant autocorrelation (0)	Significant autocorrelation (0.023)
Model-6	No significant heteroskedasticity (0.079)	No significant heteroskedasticity (0.079)	Significant autocorrelation (0)	Significant autocorrelation (0.023)
Model-7	No significant heteroskedasticity (0.073)	No significant heteroskedasticity (0.073)	Significant autocorrelation (0)	Significant autocorrelation (0.024)
Model-8	No significant heteroskedasticity (0.085)	No significant heteroskedasticity (0.085)	Significant autocorrelation (0)	Significant autocorrelation (0.024)
Model-9	Significant heteroskedasticity (0)	Significant heteroskedasticity (0)	Significant autocorrelation (0)	Significant autocorrelation (0)
Model-10	Significant heteroskedasticity (0)	Significant heteroskedasticity (0)	Significant autocorrelation (0)	Significant autocorrelation (0)
Model-11	Significant heteroskedasticity (0)	Significant heteroskedasticity (0)	Significant autocorrelation (0)	Significant autocorrelation (0)
Model-12	Significant heteroskedasticity (0)	Significant heteroskedasticity (0)	Significant autocorrelation (0)	Significant autocorrelation (0)

p-values are given in parenthesis

Source: Own calculations.

These issues can lead to biased statistical inference, as autocorrelation and heteroskedasticity result in inflated t-statistics and underestimated standard errors, potentially distorting significance levels. To address these concerns and ensure robust estimation, standard errors were clustered, providing more reliable statistical inferences.

Table 5

Likelihood Ratio Test Results for Individual & Time Effects

Model Name	Individual Fixed Effects		Time Fixed Effects		Decision
	LR Test Stat	p-Value	LR Test Stat	p-Value	
Model 1	1581.997	1.640317e-277	2034.651	0.0000	Individual and Time Effects should be included.
Model 2	1576.426	2.316828e-276	2043.184	0.0000	
Model 3	6219.715	0	115.0262	1.736867e-17	
Model 4	6193.663	0	119.7227	2.142035e-18	
Model 5	1563.803	9.333504e-274	2041.117	0	
Model 6	1565.326	4.526768e-274	2039.95	0	
Model 7	1559.979	5.740631e-273	2038.864	0	
Model 8	1578.284	9.582315e-277	2043.675	0	
Model 9	6229.878	0	144.8276	2.558587e-23	
Model 10	6192.201	0	118.5862	3.557773e-18	
Model 11	6286.236	0	159.2076	3.539369e-26	
Model 12	6323.735	0	163.4637	4.991465e-27	

Source: Own calculations.

The Likelihood Ratio (LR) test is a statistical method used to compare the fit of nested models by evaluating whether including additional parameters significantly improves the model's explanatory power. It is based on the comparison of log-likelihood values between a restricted model (without certain effects) and an unrestricted model (with those effects). The test statistic follows a chi-square ($\chi 2$) distribution, allowing for hypothesis testing.

In this study, the LR test was applied to determine the appropriate fixed effects specification (individual, time, or both) before conducting the estimations. The test results, which are given in Table 5, indicated that both individual and time effects should be included in all 12 models. This step was crucial in ensuring model accuracy by accounting for unobserved heterogeneity across regions and capturing time-specific variations, ultimately improving the reliability of the spatial panel estimations.

The Hausman test (Hausman, 1978) is a statistical procedure used to determine whether a fixed effects or random effects model provides the most efficient and consistent estimates in panel data analysis. The test evaluates whether the difference between FE and RE estimators is systematic. If the null hypothesis (H0) of no correlation between regressors and individual effects is rejected, the fixed effects model is preferred; otherwise, the random effects model is more efficient.

Table 6

Hausman Test for Each Model and Spatial Estimator

Model Name	SAR	SDM	SEM
Model-1	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-2	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-3	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 accepted– (p.val = 0.6833) (RE)
Model-4	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val = 8.025e-05) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-5	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-6	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-7	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-8	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)

Model Name	SAR	SDM	SEM
Model-9	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val = 1.99e-08) (FE)	H0 accepted– (p.val = 0.06656) (RE)
Model-10	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val.= 1.017e-08) (FE)	H0 rejected – (p.val.= 0.0001124) (FE)
Model-11	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val = 1.534e-08) (FE)	H0 rejected – (p.val: < 2.2e-16) (FE)
Model-12	H0 rejected – (p.val: < 2.2e-16) (FE)	H0 rejected – (p.val = 7.972e-09) (FE)	H0 accepted– (p.val = 0.1447) (RE)

Source: Own calculations.

In this study, the Hausman test was applied to select the appropriate effects specification for SAR, SDM, and SEM models. The results, illustrated in Table 6, indicated that for SAR and SDM models, the fixed effects specification is the most efficient. For SEM models, fixed effects were preferred in most cases, except for Models 3, 9, and 12, where the random effects specification provided the most efficient estimation. These tests ensured that the estimations accounted for possible endogeneity issues, improving the robustness and reliability of the spatial panel results.

The Bayesian Model Comparison Method using Log Marginals, proposed by LeSage (2014), is an approach for selecting the most efficient spatial model by comparing their marginal likelihoods. This method relies on Bayesian posterior probabilities and evaluates model fit by calculating the log-marginal likelihood (log-marginals), which measures how well a model explains the observed data while accounting for model complexity. A higher log-marginal value indicates a better-fitting model.

Table 7

Model Selection Based on Bayesian Comparison with Log Marginals

Model Name	Bayesian Model Comparison Method – Log Marginals	Selected Model	Model Name	Bayesian Model Comparison Method – Log Marginals	Selected Model	Model Name	Bayesian Model Comparison Method – Log Marginals	Selected Model
Model-1	SAR: 1468.2479 SDM: 1427.136 SEM: 1461.8303 SAR is the most efficient model.	SAR	**Model-5**	SAR: 1491.9622 SDM: 1481.325 SEM: 1488.5336 SAR is the most efficient model.	SAR	**Model-9**	SAR: 1107.738 SDM: 1140.341 SEM: 1095.807 SDM is the most efficient model.	SDM
Model-2	SAR: 1471.6099 SDM: 1435.933 SEM: 1465.8539 SAR is the most efficient model.	SAR	**Model-6**	SAR: 1494.6712 SDM: 1485.6690 SEM: 1491.788 SAR is the most efficient model.	SAR	**Model-10**	SAR: 1114.475 SDM: 1145.708 SEM: 1100.768 SDM is the most efficient model.	SDM
Model-3	SAR: 1106.3330 SDM: 1102.5486 SEM: 1093.377 SAR is the most efficient model.	SAR	**Model-7**	SAR: 1493.6607 SDM: 1478.484 SEM: 1489.1333 SAR is the most efficient model.	SAR	**Model-11**	SAR: 1113.434 SDM: 1139.906 SEM: 1103.019 SDM is the most efficient model.	SDM
Model-4	SAR: 1077.565 SDM: 1100.683 SEM: 1075.773 SDM is the most efficient model.	SDM	**Model-8**	SAR: 1500.3984 SDM: 1486.837 SEM: 1494.6978 SAR is the most efficient model.	SAR	**Model-12**	SAR: 1128.897 SDM: 1152.025 SEM: 1118.234 SDM is the most efficient model.	SDM

Source: Own calculations.

In this study, the method was applied to determine whether the SAR, SDM, or SEM specification provides the best representation of spatial dependence. The results, given in Table 7, showed that for Models 1, 2, 3, 5, 6, 7, and 8, the SAR model is the most efficient, while for Models 4, 9, 10, 11, and 12, the SDM specification is preferred. This approach ensured that the most appropriate spatial structure was selected for each model, enhancing the accuracy and robustness of the spatial panel estimations.

Estimation Results and Key Findings

Estimation results for SDM are presented in Table 8, while results for SAR, SEM, and the Lee-Yu transformation are shown in Table 8a, Table 8b, and Table 8c in the Appendix, respectively.

GDP(t-1): As Table 8a, 8a, 8b, 8c indicate, the one-year lagged GDP has a statistically significant and positive effect on regional growth in all models as well as those include the Lee-Yu transformation (see Yu et al., 2008; Lee & Yu, 2010a, 2010b). This confirms GDP persistence, where past economic performance influences present outcomes. This persistence is linked to capital accumulation, stable employment, ongoing business activities, and structural factors such as governance and industrial specialization. Path dependence further reinforces this effect, as past levels of income, investment, and innovation shape future economic trajectories.

Table 8

Estimations with SDM

Variable / Model Name with The Most Efficient Estimator	Model 1 Fixed Effects	Model 2 Fixed Effects	Model 3 Fixed Effects	Model 4 Fixed Effects	Model 5 Fixed Effects	Model 6 Fixed Effects	Model 7 Fixed Effects	Model 8 Fixed Effects	Model 9 Fixed Effects	Model 10 Fixed Effects	Model 11 Fixed Effects	Model 12 Fixed Effects
GDP(t-1)	0.6777 (0.0215)***	0.697 (0.0212)***			0.6977 (0.0211)***	0.6963 (0.0211)***	0.6917 (0.0213)***	0.6833 (0.0214)***				
POP	0.0005 (0.0001)***		0.0012 (0.0001)***		0.0001 (0.0001)	0.0001 (0.0001)X	0.0003 (0.0001)**	0.0004 (0.0001)***	0.0004 (0.0001)***	0.0006 (0.0001)***	0.0008 (0.0001)***	0.0011 (0.0001)***
GRAD	−0.0020 (0.0026)	−0.0017 (0.0026)	−0.0118 (0.0026)***	−0.0115 (0.0026)***	−0.003 (0.0026)	−0.003 (0.0026)	−0.0023 (0.0026)	−0.0019 (0.0026)	−0.0132 (0.0025)***	−0.0135 (0.0025)***	−0.0124 (0.0026)***	−0.0117 (0.0026)***
TO	0.0001 (0.0001)	0.0001 (0.0001)	−0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	−0.0001 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0002)	−0.0001 (0.0002)
ID(t-1)	0.0000 (0.0000)	0.0000 (0.0000)X	0.0000 (0.0000)	0.0000 (0.0000)**	0.0000 (0.0000)				1.24E-05 (5.35E-06)*			
UM(t-1)	0.0001 (0.0001)	0.0000 (0.0000)	0.0002 (0.0001)***	0.0000 (0.0001)		0.0001 (0.0000)X				0.0002 (0.0001)***		
TM(t-1)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)*	0.0000 (0.0000)			0.0000 (0.0000)*				−6.3E-06 (1.79E-06)***	
PAT(t-1)	−0.0001 (0.0001)X	0.0000 (0.0001)	−0.0002 (0.0001)**	0.0000 (0.0001)				−0.0002 (0.0000)***				−0.00031 (5.37E-05)***
rho	0.1762 (0.0575)**	0.1989 (0.0573)***	−0.4531 (0.0745)***	−0.435 (0.0753)***	0.2098 (0.0569)***	0.2128 (0.0568)***	0.1967 (0.0573)***	0.1861 (0.0573)**	−0.519 (0.0705)***	−0.5255 (0.0699)***	−0.4752 (0.0734)***	−0.4384 (0.0758)***

* denotes p-value ≤ 0.001, ** denotes 0.001 < p-value ≤ 0.01, *** denotes 0.01 < p-value ≤ 0.05, X denotes 0.05 < p-value ≤ 0.10

Robust standard errors used in estimation.

Source: Own calculations.

POP: Across all estimators and models, population density has a positive and statistically significant effect on GDP in most cases, indicating that regions with higher population density experience greater economic output. This aligns with Yanikkaya (2003), Rahman et al. (2020), and Soejoto et al. (2022). Agglomeration economies drive this relationship, as dense regions foster innovation, knowledge spillovers, and collaboration, enhancing productivity. A larger, more diverse workforce improves skill matching, while a bigger consumer base stimulates demand. Urban areas also benefit from better infrastructure and public services, further supporting economic efficiency. Despite potential drawbacks such as congestion, the net effect remains positive, particularly in urban centers.

GRAD: In SAR, SDM, and SEM models (3, 4, 9, 10, 11, and 12), where GDP(t-1) is excluded, the share of tertiary graduates has a statistically significant negative effect on GDP. This structural relationship contrasts with studies highlighting the positive impact of higher education on growth (Chatterji, 1998; Bloom et al., 2014; Tang & Lai, 2022) but aligns with Nedić et al. (2020) and partially with Maneejuk and Yamaka (2021). This suggests a potential mismatch between education and labor market needs. Insufficient high-skilled job creation may lead to underemployment or brain drain. Delayed workforce entry and an economy favoring vocational skills over university education may further explain the negative impact. If education policies prioritize quantity over quality, or curricula misalign with economic demands, the returns to education may be lower than expected.

TO: Trade openness has a positive but statistically insignificant effect in all SAR, SDM, and SEM models. However, in models 10, 11 and 12 without GDP(t-1) and in Lee-Yu transformed models, it turns negative. Furthermore, in all static and dynamic estimations using the Lee-Yu transformation, the coefficient for trade openness remains negative. The literature presents mixed findings—some report a positive impact (Jalil & Rauf, 2021; Raghutla, 2020), while others identify non-linear effects (Nguyen & Bui, 2021) or no significant relationship (Yanikkaya, 2003; Ulaşan, 2012). This study aligns with Yanikkaya (2003) and Ulaşan (2012), suggesting that trade liberalization alone does not guarantee economic growth. This finding contrasts with some regional analyses of China, where greater trade openness was found to be a significant and robust driver of innovation at the provincial level, especially in more developed coastal regions (Qayyum et al., 2022). The composition of trade matters—low-value-added exports or reliance on capital-intensive imports may limit gains. Weak domestic competitiveness, deindustrialization, institutional bottlenecks, and policy instability further dilute benefits. Trade openness often involves an adjustment period; the negative effect in Lee-Yu transformed models suggests interactions with omitted factors like intellectual property, technology, or innovation capacity. Overall, trade openness alone is insufficient; complementary policies and structural reforms are necessary to unlock its full potential.

ID(t-1): One-year lagged design registrations positively impact GDP across all models, with statistical significance in Models 3 and 9 under SAR and SEM estimations (Models 2, 3, 4, 9) and in Models 2, 4, and 9 under SDM. The effect is also significant in models applying the Lee-Yu transformation. However, models incorporating GDP(t-1) and those without isolated IPR variables yield insignificant results, likely due to suppression effects from high correlations. Despite this, the SDM estimator—identified as the most efficient—confirms the positive effect, reinforcing the conclusion that design registrations contribute to GDP.

The positive effect suggests that industrial design investments enhance economic growth by improving product differentiation, increasing consumer demand, and boosting exports. These effects materialize over time, as design innovations require a lag before impacting market performance.

UM(t-1): Similar to design registrations, lagged utility model registrations positively influence GDP, with statistical significance in Models 3, 6, and 10 under SAR, SEM, and SDM estimations, as well as in Models 3 and 10 when the Lee-Yu transformation is applied. The SDM estimator and isolated models confirm this relationship, reinforcing the broader findings.

Utility models, or "petty patents," support incremental innovation, leading to cost reductions, efficiency gains, and greater competitiveness. Their shorter approval process enables firms to commercialize innovations quickly, facilitating faster economic benefits. The observed time lag highlights that these innovations take time to integrate into production and markets.

TM(t-1): The relationship between lagged trademark registrations and GDP is mixed. While a significant negative effect appears in Model 11, positive effects emerge in Models 3 and 7, as well as under the Lee-Yu transformation in Models 3, 4, and 11. A negative effect is found in Model 7 under dynamic estimation. The variation in sign suggests that trademark registrations' impact depends on market structure, brand saturation, and economic conditions.

The negative effect may stem from excessive trademarking as a defensive strategy rather than a driver of economic activity. Additionally, trademarks often reflect competition rather than direct innovation, meaning that brand protection may not necessarily translate into higher productivity. In cases where dominant brands create entry barriers, the expected growth-enhancing effects may be limited.

PAT(t-1): Patent registrations show a predominantly negative relationship with GDP across general SAR, SEM, and SDM models. Under the Lee-Yu transformation, negative coefficients appear in Models 3 and 8, while positive effects are observed in Models 4 and 12. However, patents consistently yield negative coefficients in general models, with the negative effect also confirmed in Model 8 under dynamic estimation.

This suggests that while patents protect intellectual property, their economic benefits are not always immediate. Long approval processes, high costs, and strategic patent accumulation may slow innovation diffusion, delaying productivity gains. Additionally, patents often concentrate in capital-intensive sectors, which may not immediately benefit broader economic growth.

The findings on intellectual property rights align with previous research but diverge in Türkiye's case. While Kim et al. (2012), Prud'homme (2017), and Bulus & Bakirtas (2021) found patents negatively and utility models positively impacting developing economies, Bulus & Bakirtas (2021) found no significant effect in Türkiye. In contrast, Bielig (2015) reported positive patent and negative utility model effects in Germany, reflecting a developed economy's characteristics. The results of this study support the notion that patents benefit high-tech economies, while utility models are more relevant for developing nations like Türkiye.

The negative effect of trademark registrations may stem from entry barriers created by dominant brands, limited consumer benefits from new brands, and weak growth-enhancing effects from branding. Bozkaya et al. (2020) found no statistical effect of trademarks on Türkiye's economic growth, while Ökten et al. (2019) suggested that branding's impact is more long-term. Due to data limitations, this study could not analyze long-term trademark effects, and the absence of fully developed co-integration tests for spatial panel models restricts further exploration.

Utility models and industrial designs are often preferred by SMEs and local businesses due to faster commercialization, lower R&D costs, and an application-driven nature. Patents, on the other hand, require long-term investments, deterring firms with limited capital. Türkiye's comparative advantage in low- and medium-tech production (Şaşmaz, 2024a, 2024b) explains why utility models positively contribute to growth, while patents impose higher costs than benefits. Abay et al. (2021) support this view, noting that most Turkish patents target low-tech products, limiting their economic impact. Similarly, the branding of lower-quality goods may not generate significant short-term economic benefits.

Interpretation of IPR Effects in Theoretical Context

Schumpeterian Growth Theory suggests that incremental innovations—reflected in utility model and industrial design registrations—enhance firm productivity and economic development, particularly in environments with weak high-tech R&D. Their positive effect indicates that frequent yet minor improvements in product design and functionality drive growth. In contrast, the negative impact of patents and trademarks suggests that rigid intellectual property protections, when applied to low-quality or undifferentiated products, fail to generate meaningful technological advancements. In Türkiye, where firms prioritize cost-cutting over high-value innovation, excessive patenting may function as a defensive mechanism rather than a driver of technological progress, limiting creative destruction and slowing innovation diffusion in a way that can stifle competition (Encaoua et al., 2006).

Market Power Theory explains these contrasting results by highlighting how strong patent and trademark protections can create monopolistic advantages. Rather than incentivizing R&D, they may encourage rent-seeking behaviors, where firms focus on protecting market dominance rather than reinvesting in innovation. This dynamic is particularly noted with trademark overuse, which can enable firms to exert market control and reduce overall economic efficiency (Schautschick & Greenhalgh, 2016). Türkiye's industrial landscape, with firms relying on imitation rather than genuine R&D, struggles under such an IPR system. In contrast, utility model and industrial design protections, which provide shorter and less restrictive rights, foster competition and encourage rapid, incremental innovation. Their suitability for economies driven by quick adaptations rather than deep R&D investments explains their positive impact.

The Innovation Spillover Hypothesis further contextualizes these findings. While patents theoretically incentivize R&D, in weak research ecosystems like Türkiye, they may instead act as barriers to knowledge sharing. Similarly, trademarks, while valuable for branding, do not contribute to technological progress if the underlying products remain low in quality or lack differentiation. Conversely, utility models and industrial designs, with their less restrictive protection and faster innovation cycles, may promote knowledge spillovers and accelerate the diffusion of economic benefits, allowing firms to build on shared advancements while maintaining competitive incentives (Prud'homme, 2017).

Overall, the results align with different economic theories. Schumpeterian Growth Theory supports the positive effect of utility models and industrial designs but contradicts the expected role of patents and trademarks. Market Power Theory explains why excessive patenting and trademarking hinder competition, while the Innovation Spillover Hypothesis reinforces the notion that patents restrict technology diffusion in Türkiye's weak R&D environment.

The spatial panel data results, illustrated in Table 8a and Appendix, also have theoretical implications. The findings reveal both positive and negative spillover effects, suggesting a complex regional dynamic. Some cities appear to stimulate regional growth through innovation diffusion, while others may concentrate benefits locally, limiting spillovers. This aligns with the work of Jaffe (1986), who emphasized that spatial proximity is a key factor in knowledge diffusion. The results support the view that strong industrial and institutional linkages between regions enhance positive externalities, while weaker networks can restrict the spread of economic gains.

Additional Remarks on the Model

The spatial parameter is statistically significant across all estimators, indicating a positive spillover effect in most models. However, models 9–12 under the SDM estimator display negative spillover effects, requiring closer examination. Since analyzing the effects across all models and estimators would exceed the scope of this study, the direct, indirect, and total impacts of models 9, 10, 11, and 12 under the SDM estimator which is identified as the most efficient are presented in Table 9.

Population density and the share of tertiary graduates are statistically significant across all models, with positive and negative coefficients, respectively, while trade openness remains insignificant. For IPR variables, design and utility model registrations have positive effects, whereas trademarks and patents exhibit negative effects in models 9 and 10.

The SDM estimator confirms that a city's GDP is influenced by both local characteristics and spatial spillovers from neighboring regions. GDP is positively affected by population density, design, and utility model registrations, while the share of tertiary graduates, trademarks, and patents exert negative effects. These patterns persist across neighboring regions, reinforcing the spatial spillover mechanism. Notably, trade openness remains statistically insignificant both locally and in neighboring areas.

A comparison of models highlights that GDP(t-1) overshadows other explanatory variables, suggesting strong economic persistence. To prevent this masking effect, models 9–12 exclude GDP(t-1) and introduce IPR variables separately. This approach ensures that interdependencies among IPR variables do not distort results, allowing for a clearer evaluation of their individual effects on GDP.

Spatial Impact Results and Analysis

The positive spillover effect of population density indicates that densely populated cities drive both their own economic performance and that of neighboring regions through agglomeration economies, labor mobility, and regional market integration. These areas generate demand for goods and services beyond city boundaries, fostering trade, business expansion, and knowledge spillovers. The detection of such significant spatial interdependencies in Türkiye is consistent with recent regional-level research in other large emerging economies. For example, studies in China have also confirmed that IPR policies and university innovation activities create significant positive economic spillovers in neighboring counties and regions (Gu, 2023; Yu & Shen, 2024). Conversely, the negative spillover effect of tertiary graduates suggests that a high concentration of educated individuals does not necessarily benefit neighboring cities. This may be due to brain drain toward major urban centers or a mismatch between education levels and local labor market needs, leading to underemployment. Instead of fostering regional spillovers, high education levels in one city may widen spatial labor market disparities.

Table 9

Impact Analysis

SDM	Variables	Direct Impact			Indirect Impact			Total Impact		
		Coefficient	p-value	Sig.	Coefficient	p-value	Sig.	Coefficient	p-value	Sig.
Model-9	POP	0.00044385	5.8042E-13	***	0.00135984	8.5117E-06	***	0.0018037	2.4153E-07	***
	GRAD	−0.01324951	1.8372E-07	***	−0.04059298	5.6183E-05	***	−0.05384249	8.4099E-06	***
	TO	-7.4731E-05	0.68907239		−0.00022896	0.68975842		−0.00030369	0.68889099	
	ID(t-1)	1.241E-05	0.01323011	*	3.8022E-05	0.0221709	*	5.0432E-05	0.01800708	*
Model-10	POP	0.00061177	2.2204E-15	***	0.00185248	9.2144E-07	***	0.00246425	7.0696E-09	***
	GRAD	−0.01350069	1.383E-07	***	−0.04088097	4.2235E-05	***	−0.05438167	5.6962E-06	***
	TO	−8.2202E-05	0.55906155		−0.00024891	0.55523401		−0.00033112	0.55496394	
	UM(t-1)	0.00021022	0.00015732	***	0.00063655	0.00224119	**	0.00084677	0.00097478	***
Model-11	POP	0.00076264	2.1772E-11	***	0.00216721	1.4499E-05	***	0.00292986	4.1398E-07	***
	GRAD	−0.01235171	3.0017E-06	***	−0.03509999	0.00019095	***	−0.0474517	3.9392E-05	***
	TO	−0.00010289	0.48678767		−0.00029238	0.48625874		−0.00039527	0.48478445	
	TM(t-1)	−6.3145E-06	0.0011104	**	-1.7944E-05	0.00346316	**	-2.4258E-05	0.00199831	**
Model-12	POP	0.0010784	6.6613E-16	***	0.00278354	5.1994E-06	***	0.00386194	2.6731E-08	***
	GRAD	−0.01165759	1.446E-05	***	−0.03009042	0.00042746	***	−0.04174801	0.00010462	***
	TO	−0.00011422	0.45046914		−0.00029481	0.45031797		−0.00040903	0.44843822	
	PAT(t-1)	−0.00031363	6.8227E-08	***	−0.00080953	0.00022112	***	−0.00112316	2.1723E-05	***

Source: Own calculations.

The statistical insignificance of trade openness in models 9-12 implies that Türkiye's regional economic linkages are primarily driven by domestic intercity interactions rather than international trade.

The positive spatial impact of design and utility model registrations suggests that product differentiation and incremental innovation diffuse beyond their originating cities. These innovations spread through business networks, supplier linkages, and industrial knowledge sharing, enhancing regional productivity.

In contrast, the negative spillover effects of trademark and patent registrations indicate that their benefits are not effectively shared across neighboring regions. Trademark registrations may encourage defensive branding and monopolistic strategies, limiting competition and restricting market entry. Patents, while promoting innovation, may also lead to technology hoarding, high licensing costs, and legal barriers, preventing firms in surrounding areas from accessing and implementing new advancements. This reinforces economic concentration rather than fostering regional growth.

Policy Implications

The persistence of GDP growth highlights the need for long-term investments in infrastructure, technology, and capital accumulation. Policymakers should focus on projects that support stable employment and industrial activity by investing in critical digital infrastructure, such as expanding high-speed broadband to organized industrial zones, and modern logistics networks that connect production centers to export hubs. To enhance access to finance for capital-intensive businesses, concrete actions could include establishing government-backed loan guarantees for firms investing in high-technology manufacturing or creating a National Technology Investment Fund that co-invests with private venture capital to de-risk innovative projects.

The positive effect of population density underscores the benefits of urbanization. Investments in infrastructure, connectivity, and public services can enhance productivity, innovation, and skill matching. However, Şaşmaz (2025) highlights that increased population density may also contribute to income inequality, necessitating balanced policies to ensure equitable development.

The negative impact of tertiary graduates on GDP suggests that education policies must align with labor market needs. Expanding vocational and technical education, strengthening university-industry collaboration, and promoting entrepreneurship initiatives can improve workforce readiness and job creation. This is particularly relevant in an economy like Türkiye's, where the industrial sector may demand more vocational and technical skills than the service sector can absorb from a growing pool of tertiary graduates. Specifically, this could involve a strategic review of higher education programmes, potentially adjusting student quotas, or consolidating departments with persistently low graduate employment rates to better match the labor market's technical and vocational demands. Furthermore, entrepreneurship support should be bolstered through targeted grants, mentorship programmes, and incubation support for recent graduates to encourage self-employment and new job creation. Additionally, higher education programmes that fail to generate employment or economic value should be restructured.

The insignificance of trade openness in growth models suggests that trade liberalization alone is insufficient for economic expansion. Export diversification, targeted industrial incentives, and institutional improvements are needed to enhance global competitiveness. Strategic trade agreements should focus on market access and industrial resilience.

The positive effect of design and utility model registrations reinforces the value of incremental innovation. Policies should streamline registration processes, offer direct financial support, such as tax incentives or application fee subsidies, particularly for Small and Medium-sized Enterprises (SMEs), strengthen IPR enforcement, and foster collaboration between businesses and research institutions to accelerate commercialization and maximize economic gains.

Given the mixed effects of trademark registrations, policymakers must prevent defensive branding strategies that hinder competition. Instead, trademarks should be integrated into broader business expansion and internationalization strategies to maximize economic returns.

The negative impact of patent registrations suggests inefficiencies in the patent system. Simplifying approval processes, promoting technology transfer, and discouraging strategic patenting practices that stifle competition can enhance economic benefits. Supporting SMEs and start-ups in commercializing patented innovations through dedicated SME support funds, university-industry technology transfer offices, and subsidized legal assistance will further strengthen the patent system's contribution to growth.

Effective implementation of these policies is expected to generate significant spillover effects, fostering regional economic convergence. Investments in infrastructure and industry enhance connectivity, reducing trade and transportation costs for neighboring cities. Population density and labor mobility facilitate workforce integration, while aligning education with labor market needs ensures talent diffusion. Encouraging innovation hubs and knowledge clusters will further support regional collaboration, integrating cities into broader value chains and promoting sustainable economic development.

Finally, given the strong evidence of spatial spillovers in this study, policymakers should move beyond city-specific incentives and actively foster regional collaboration. A concrete measure would be the establishment of Regional Innovation and Patent Alliances to unite universities, businesses, and local governments across neighboring provinces. This approach is supported by recent research on China that recommends creating regional alliances to formalize knowledge sharing between institutions (Gu, 2023). For Türkiye, such alliances could facilitate joint R&D projects, coordinate technology transfer, and create integrated regional value chains. The government could act as a macro-regulator, providing the top-level policy design and initial funding to launch these collaborative innovation ecosystems.

Conclusion

This study provides empirical evidence on the determinants of regional economic growth in Türkiye, with a particular focus on GDP persistence, population density, trade openness, education, and IPRs. Utilizing spatial panel data analysis with SAR, SDM, and SEM estimations in both static and dynamic settings, this study ensures robust results. Covering the period 2008–2023, it examines 81 cities at the NUTS-III level, offering a comprehensive analysis of Türkiye's regional economic dynamics. The findings highlight both expected and nuanced relationships between these factors and economic performance, shedding light on the structural and institutional dynamics shaping regional economies. The presence of statistically significant spatial autocorrelation further indicates that neighboring cities influence each other's economic performance, highlighting the role of regional spillovers in growth dynamics.

The persistence of GDP across periods is confirmed, with one-year lagged GDP exhibiting a positive and statistically significant impact across all models. This result aligns with the notion that economic momentum, capital accumulation, and institutional continuity reinforce regional growth trajectories over time. Similarly, population density consistently demonstrates a positive effect on GDP, underscoring the importance of agglomeration economies, labor market efficiencies, and infrastructure advantages in driving economic output.

However, the study uncovers a counterintuitive relationship between tertiary education and GDP, where a higher share of university graduates in the population correlates negatively with economic performance. This result suggests possible mismatches between labor market needs and the supply of high-skilled workers, as well as structural constraints that hinder the productive utilization of tertiary education. These findings align with studies indicating that education-driven growth depends on the quality of human capital, economic absorptive capacity, and alignment with industrial needs.

Trade openness, despite being widely regarded as a driver of economic growth, does not yield a statistically significant impact in this study. While some models suggest a negative effect, particularly when GDP persistence is not accounted for, the results align with literature emphasizing that trade liberalization alone is insufficient for growth. Factors such as trade composition, industrial competitiveness, and institutional capacity play crucial roles in determining whether trade openness translates into economic benefits.

The role of IPRs in economic growth presents a complex picture. One-year lagged design and utility model registrations positively influence GDP, suggesting that incremental innovations and industrial designs contribute to economic performance. These results align with Schumpeterian Growth Theory and the Innovation Spillover Hypothesis, as less complex forms of innovation—such as utility models—are particularly effective in developing economies where rapid adaptation and commercialization are crucial. Conversely, patent registrations predominantly exhibit a negative effect, indicating that the costs, legal barriers, and strategic use of patents may outweigh their immediate economic benefits. This finding supports the view that patenting is more beneficial in advanced economies, where well-developed innovation ecosystems facilitate the transformation of patents into marketable products.

Similarly, trademark registrations yield mixed results, with some models indicating a negative effect on GDP. This suggests that brand proliferation does not always lead to economic gains, particularly when trademark strategies prioritize market control rather than productivity and innovation. These findings highlight the importance of market structure and competition dynamics in determining the economic impact of branding. As with patents, Market Power Theory provides a relevant framework for interpreting these results, as it suggests that strong patenting and branding can lead to market concentration, reduce competition, and potentially limit consumer choice.

Overall, this study highlights the need for nuanced policy approaches to economic growth. Policies should not only focus on promoting trade openness, higher education, and intellectual property protection in a general sense but also ensure that these elements align with regional economic structures and industrial capabilities. Strengthening the link between education and labor market needs, fostering innovation through targeted IPR policies, and addressing structural constraints in trade and competition could enhance the effectiveness of economic strategies. By incorporating spatial econometric techniques and both static and dynamic perspectives, this study provides robust empirical insights into regional economic development. Its findings contribute to the broader literature on regional growth, particularly in transition economies like Türkiye, where the interplay of institutional, demographic, and innovation-related factors continues to shape economic trajectories.

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Appendix

Table 8a

Estimations with SAR

Variable / Model Name with The Most Efficient Estimator	Model 1 Fixed Effects	Model 2 Fixed Effects	Model 3 Fixed Effects	Model 4 Fixed Effects	Model 5 Fixed Effects	Model 6 Fixed Effects	Model 7 Fixed Effects	Model 8 Fixed Effects	Model 9 Fixed Effects	Model 10 Fixed Effects	Model 11 Fixed Effects	Model 12 Fixed Effects
GDP(t-1)	0.6467 (0.0206) ***	0.6636 (0.0202)			0.6616 (0.0204) ***	0.6597 (0.0205) ***	0.6577 (0.0204) ***	0.651 (0.0205) ***				
POP	0.0005 (0.0001) ***		0.0014 (0.0002) ***		0.0001 (0.0001)	0.0001 (0.0001)X	0.0003 (0.0001) **	0.0004 (0.0001) ***	0.0004 (0.0001) ***	0.0006 (0.0001) ***	0.0009 (0.0001) ***	0.0012 (0.0001) ***
GRAD	−0.0017 (0.0024)	−0.0012 (0.0024)	−0.0127 (0.0032) ***	−0.0123 (0.0033) ***	−0.0026 (0.0024)	−0.0027 (0.0024)	−0.0019 (0.0024)	−0.0016 (0.0024)	−0.0154 (0.0032) ***	−0.0155 (0.0032) ***	−0.0137 (0.0032) ***	−0.0125 (0.0032) ***
TO	0.0001 (0.0001)	0.0002 (0.0001)	0.0000 (0.0002)	0.0002 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)	0.0000 (0.0002)
ID(t-1)	0.0000 (0.0000)	0.0000 (0.0000)*	0.0000 (0.0000)X	0.0000 (0.0000) **	0.0000 (0.0000)				1.27E 05(6.02 E-06)*			
UM(t-1)	0.0001 (0.0001)	0.0000 (0.0000)	0.0002 (0.0001)**	0.0000 (0.0001)		0.0001 (0.0000)X				0.0002 (0.0001) ***		
TM(t-1)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)*	0.0000 (0.0000)			0.0000 (0.0000)**				−8.5E-06 (1.95E-06) ***	
PAT(t-1)	−0.0001 (0.0001)X	0.0000 (0.0000)	−0.0003 (0.0001) ***	0.0000 (0.0001)				−0.0002 (0.0000) ***				−0.0004 (5.7E-05) ***
rho	0.3149 (0.0261) ***	0.3305 (0.0259) ***	0.4958 (0.0295) ***	0.5388 (0.0284) ***	0.3154 (0.0262) ***	0.3127 (0.0263) ***	0.3151 (0.0263) ***	0.3149 (0.0261) ***	0.5043 (0.0296) ***	0.4979 (0.0298) ***	0.5025 (0.0296) ***	0.4991 (0.0295) ***

Notes: *, **, *** denote statistical significance levels; X denotes 10% level. Robust standard errors used in estimation.
Source: Own calculations.

Table 8b

Estimations with SEM

Variable / Model Name with The Most Efficient Estimator	Model 1 Fixed Effects	Model 2 Fixed Effects	Model 3 Random Effects	Model 4 Fixed Effects	Model 5 Fixed Effects	Model 6 Fixed Effects	Model 7 Fixed Effects	Model 8 Fixed Effects	Model 9 Random Effects	Model 10 Fixed Effects	Model 11 Fixed Effects	Model 12 Random Effects
GDP(t-1)	0.6467 (0.0206)	0.6636 (0.0202) ***			0.6616 (0.0204) ***	0.6597 (0.0205) ***	0.6577 (0.0204) ***	0.651 (0.0205) ***				
POP	0.0005 (0.0001)		0.0014 (0.0002) ***		0.0001 (0.0001)	0.0001 (0.0001)X	0.0003 (0.0001) **	0.0004 (0.0001) ***	0.0004 (0.0001) ***	0.0006 (0.0001) ***	0.0009 (0.0001) ***	0.0012 (0.0001) ***
GRAD	−0.0017 (0.0024)	−0.0012 (0.0024)	−0.0127 (0.0032) ***	−0.0123 (0.0033) ***	−0.0026 (0.0024)	−0.0027 (0.0024)	−0.0019 (0.0024)	−0.0016 (0.0024)	−0.0132 (0.0025) ***	−0.0155 (0.0032) ***	−0.0137 (0.0032) ***	−0.0125 (0.0032) ***
TO	0.0001 (0.0001)	0.0002 (0.0001)	0.0000 (0.0002)	0.0002 (0.0002)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	−0.0001 (0.0002)	0.0001 (0.0002)	0.0000 (0.0002)	0.0000 (0.0002)
ID(t-1)	0.0000 (0.0000)	0.0000 (0.0000)*	0.0000 (0.0000)X	0.0000 (0.0000) **	0.0000 (0.0000)				1.27E-05(6.02E-06)*			
UM(t-1)	0.0001 (0.0001)	0.0000 (0.0000)	0.0002 (0.0001) **	0.0000 (0.0001)		0.0001 (0.0000)X				0.0002 (0.0001) ***		
TM(t-1)	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)*	0.0000 (0.0000)			0.0000 (0.0000) **				−8.5E-06 (1.95E-06) ***	
PAT(t-1)	−0.0001 (0.0001)	0.0000 (0.0001)	−0.0003 (0.0001) ***	0.0000 (0.0001)				−0.0002 (0.0000) ***				−0.00039 (5.7E-05) ***
lambda	0.3149 (0.0261)	0.3305 (0.0259) ***	0.4958 (0.0295) ***	0.5388 (0.0284) ***	0.3154 (0.0262) ***	0.3127 (0.0263) ***	0.3151 (0.0263) ***	0.3149 (0.0261) ***	0.5043 (0.0296) ***	0.4979 (0.0298) ***	0.5025 (0.0296) ***	0.4991 (0.0295) ***

* denotes p-value ≤ 0.001, ** denotes 0.001 < p-value ≤ 0.01,
*** denotes 0.01 < p-value ≤ 0.05, X denotes 0.05 < p-value ≤ 0.10

Robust standard errors used in estimation.

Source: Own calculations.

Table 8c

Estimations with LeE-Yu Transformation

Variable / Model Name with The Most Efficient Estimator	Model 1 SAR Fixed Effects	Model 2 SAR Fixed Effects	Model 3 SAR Fixed Effects	Model 4 SDM Fixed Effects	Model 5 SAR Fixed Effects	Model 6 SAR Fixed Effects	Model 7 SAR Fixed Effects	Model 8 SAR Fixed Effects	Model 9 SDM Fixed Effects	Model 10 SDM Fixed Effects	Model 11 SDM Fixed Effects	Model 12 SDM Fixed Effects
GDP(t-1)	0.6553 (0.0093) ***	0.6669 (0.0093) ***			0.666 (0.0518) ***	0.6649 (0.0508) ***	0.6627 (0.0093) ***	0.6584 (0.1543) ***				
POP	0.0003 (0.0001) ***		0.0014 (0.0002) ***		0.0001 (0.0001)	0.0002 (0.0001)X	0.0002 (0.0001) **	0.0003 (0.0001) ***	0.0024 (0.0004) ***	0.0024 (0.0002) ***	0.0015 (0.0003) ***	0.0012 (0.0007)X
GRAD	−0.0013 (0.012)	−0.0002 (0.0118)	−0.0128 (0.0156)	−0.0362 (0.0139) **	−0.0022 (0.003)	−0.0022 (0.0028)	−0.0014 (0.012)	−0.0012 (0.0028)	−0.0308 (0.0509)	−0.031 (0.0061) ***	−0.0342 (0.0134) *	−0.0354 (0.0107) ***
TO	0.0001 (0.0002)	0.0002 (0.0002)	0.0000 (0.0002)	−0.0009 (0.0003) **	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	−0.001 (0.0003) **	−0.0009 (0.0003) **	−0.001 (0.0003) **	−0.0009 (0.0004) *
ID(t-1)	7.12E-06 (5.03E-06)	8.42E-06(5.03E-06)X	0.0000 (0.0000)X	0.0000 (0.0000)	5.06E-06(4.53E-06)				1.79E-05 (6.02E-06) **			
UM(t-1)	3.63E-05 (5E-05)	1.77E-06(4.92E-05)	0.0002 (0.0001) **	0.0002 (0.0001)		6.74E-05(4.18E-05)				0.0003 (0.0001) *		
TM(t-1)	−1.8E-06 (2.09E-06)	−6.1E-07(2.07E-06)	0.0000 (0.0000) *	0.0000 (0.0000) *			−2.8E-06 (1.33E-06) *				1.59E-05 (5.28E-06) **	
PAT(t-1)	−7E-05 (5.94E-05)	−2E-05(5.84E-05)	−0.0003 (0.0001) **	0.0007 (0.0002) ***				−0.0001 (0.0001)X				0.0004 (0.0002) **
rho	0.386743 (0.009279) ***	0.3997 (0.0093) ***	0.4897 (0.0119) ***	0.4697 (0.0117) ***	0.3907 (0.05) ***	0.3897 (0.2301)X	0.3957 (0.0093) ***	0.3897 (0.2188)X	0.3977 (0.0735) ***	0.3977 (0.0322) ***	0.4067 (0.0118) ***	0.4197 (0.2884)

* denotes p-value ≤ 0.001, ** denotes 0.001 < p-value ≤ 0.01, *** denotes 0.01 < p-value ≤ 0.05, X denotes 0.05 < p-value ≤ 0.10

Robust standard errors used in estimation.

Source: Own calculations.