REGION
The Journal of ERSA
Powered by WU

Volume 12, Number 1, 2025, 1–18
DOI: 10.18335/region.v12i1.521
journal homepage: region.ersa.org
ISSN: 2409-5370

Spillover Effects of Public Capital Stock: A Case Study for Ecuador

Roberto Zurita[1], Víctor Morales-Oñate[2]

[1] Universidad San Francisco de Quito, Quito, Ecuador
[2] Universidad de las Américas, Quito, Ecuador

Received: 5 November 2023/Accepted: 13 January 2025

Abstract. This research examines the spatial spillovers of public capital on gross value added across 216 cantons in continental Ecuador. The investigation is conducted within the framework of Spatial Econometrics, utilizing various model specifications and spatial weight matrices, complemented by a Cobb Douglas-type model that incorporates spatial dependence. The findings highlight a positive spatial impact of the public capital stock, with approximately 30% of the overall effect attributed to the indirect component. This underscores the importance of considering spatial structure when assessing the effects of capital on gross value added. Consequently, the study extends its exploration to derive column and row effects, aimed at identifying the most influential cantons within the neighborhoods established by the spatial structure.

1 Introduction

The literature has found evidence of the effects of public capital on the economic performance of countries, as it is a factor that, together with private capital, labor and technology, contributes to productive performance. However, new research in the field of new economic geography has revealed that these factors can spread their effect in spatial dimensions to nearby territories.

Spatial economics seeks to explain the causes of the unequal distribution of wealth among territories, understanding what factors attract and concentrate economic activities to a site and what forces cause their dispersion. This field of study allows us to incorporate the conceptual framework of economics in the spatial dimension, in order to understand economic phenomena at the regional level (Marrocu, Paci 2010).

According to economic orthodoxy, it is known that the level of production of a country depends on factors such as labor, capital stock and technology. In relation to the capital that a country possesses, we understand the means of production that companies possess to produce, but we must also take into account the stock of public capital, since it has been inferred that investment in public infrastructure such as roads, railroads, basic services, among others, contribute to lowering the production costs of companies and allow mobilizing labor to production centers, thus improving the economic performance of the regions (Fingleton 2001).

Most developed countries present spatial economic structures that base value generation on research, innovation, high-tech industry, service provision, etc. On the other hand, developing countries largely maintain a productive matrix based on the generation of primary goods linked to natural resources, and with a low level of productive linkages.

This has influenced the way in which their economic activities have been distributed throughout their territories, and the way in which they interact with each other. Within this dynamic, it is of special interest to analyze how production factors such as public capital influence economic performance in the territories of a developing country, and how their effect can spread to nearby spatial units.

The literature has found evidence of the effects of public capital on the economic performance of countries, being a factor that together with private capital, labor and technology contribute to productive performance. However, new research in the field of new geographical economics and spatial economics such as Han et al. (2016) have revealed that these factors can spread their effect in spatial dimensions to nearby territory.

The majority of research defines public capital as the physical assets owned by the government, excluding military-related assets (Bom, Ligthart 2014). This implies that both public and private capital play a role in creating a conducive economic environment. Consequently, there has been significant scholarly endeavor aimed at quantifying the impact of public capital on economic performance.

Mera (1973) stands as one of the initial contributors to the field, delving into the impacts of public capital. Employing econometric techniques with both additive and multiplicative production functions, this study utilized ordinary least squares. Notably, Mera's research unearthed early signs that the influence of production elasticity concerning public capital heavily relies on how this variable is defined. Notably, elasticities demonstrated notably higher values when encompassing transportation infrastructure. The study was conducted across 46 Japanese prefectures during the span of 1954 to 1963. Although evidence has been found that public capital improves the economic performance of regions, it is necessary to categorize it. Not all public investment has a significant influence on firm productivity.

Bom, Ligthart (2014) categorize public capital into two groups: i) Central or core, which includes highly productive infrastructure like roads, railways, and airports, as well as key public services such as sewage and water systems due to their direct impact on economic activity, and ii) Non-central or peripheral, which encompasses other public services and structures, including hospitals, educational facilities, and various other public buildings. Aschauer (1989) delves into the distinct impacts of core and non-core public capital. Employing the production function, he sought to understand the decline in productivity growth in the US during the 1970s. He discovered that a 1% rise in the core public capital stock led to a 0.39% boost in private production. This significant figure indicates that public capital played a pivotal role in influencing production.

Berndt, Hansson (1992) concentrate exclusively on the role of core capital in enhancing the private sector's productivity performance. They investigated how it reduced production costs within the Swedish economy during the 1980s. One of their significant findings was that core public infrastructure played a pivotal role in cost reduction for the private sector. Through counterfactual simulations, they demonstrated that the Swedish economy could have mitigated its productivity slowdown by 6.1% if it had adhered to optimal public spending levels. In doing so, the authors identified a mechanism through which public investment could enhance the productivity of the private sector.

Since that time, many studies have been conducted for the United States as well as several OECD nations. More recently, the impact of public capital on productivity in developing countries has also garnered attention. Ram (1996) examined the roles of both public and private capital in these countries throughout the 70s and 80s. His findings suggest that during the 70s, private capital outperformed public capital in terms of productivity. However, in the 80s, public capital took the lead, contributing more to production than private capital.

Guevara (2016) demonstrates through spatial econometric methods that urban agglomerations generate a spatial spillover effect of their economic growth to their neighboring regions in Latin American countries such as Argentina, Bolivia, Chile, Colombia, Ecuador, Mexico, Peru and Panama. However, the sample used does not include all the regions of the countries analyzed. Álvarez et al. (2016) perform a spatial econometric analysis to determine the spillover effects of public capital as a factor of the production function for the regions of Spain for the periods 1980-2007. The findings show that transportation infrastructure generates a positive and significant spillover effect across regions. Jia et al. (2020) conduct a spatial analysis between factors of different production functions among rural regions in Taizhou municipality in China, finding evidence of spatial correlation between regions with different production patterns.

In the context of Ecuador, research has been conducted to evaluate the elasticities of GDP in relation to production factors like capital and labor. Briones Bendoza et al. (2018) undertook an analysis of the variations in these factors from 1950 to 2014. They employed an econometric approach, leveraging ordinary least squares. Their findings suggest that physical capital plays a more significant role in production compared to labor. This trend might be attributed to the nation's dominant economic activities relying on low-skilled, low-wage labor, thus amplifying the relative contribution of capital. However, this study does not distinguish between public and private capital, making it challenging to discern the specific contributions of each. Moreover, the study's capital variable represents gross capital, encompassing both private and public capital, including its core, non-core, and military segments. In light of this, as per Bom, Ligthart (2014) and Aschauer (1989), the non-core capital likely has limited influence on production, and military expenditure is anticipated to be non-influential.

Moreno Loza (2017) delves into the implications of fiscal policy in Ecuador between 2000 and 2015, aiming to assess the impact of current spending, capital spending and tax revenue on gross domestic product (GDP). This investigation employs the VARS (structural vector autoregressive) model for the analysis. The predominant findings indicate that fiscal modifications directed towards capital expenditure yield a multiplier effect of 0.37 on GDP, marking it as the most influential category. Conversely, alterations in current public expenditure yield a multiplier effect of 0.11 on GDP. It is worth noting that this study primarily focuses on a national scope, without exploring the resultant effects on economic performance or the productivity discrepancies across different regions.

Most of the cited literature on the evidence of economic spillover effects from public capital has been conducted in industrialized countries with higher levels of public capital stocks compared to those in a developing economy such as Ecuador. In a spatial econometrics setting, growth within a specific region is determined by the independent variables across all other regions within the system. This is the mechanism by which public capital in one canton can influence on the economic growth of neighbors. Therefore, this research contributes to finding evidence of contagion effects in a developing economy and understanding how these economic effects are transmitted among its regions. Indirect effects are spillover effects and direct effects include feedback effects. Spatial dependence structure is examined by setting different weights matrices. Finally, differentiating private and public capital across 216 cantons in continental Ecuador implied a detailed information gathering exercise which let us apply spatial models.

This paper seeks evidence that a production factor such as public capital can generate spatial effects on the production levels of the different cantons of Ecuador. For this purpose, a spatial econometric analysis is carried out through different types of models that allow sensitizing the economic analysis of the production factors with the geographic structures that can generate effects on the economic dynamics of a nation. To this end, data were collected for the year 2017 from 216 cantons nationwide.

The results show that, although public capital does not directly affect production in neighboring cantons, it does so indirectly by affecting production levels in its canton of origin, since evidence was found that production levels have a positive spatial correlation between cantons. In addition, evidence was found that the ability to propagate this effect does not depend solely on the size or economic relevance of the canton, but that there are additional characteristics that should be investigated.

The contribution of this study is relevant because, as far as the literature review has shown, it is the first approach in Ecuador to determine the spatial effects of the factors of production of a developing economy, and it also allows us to see which cantons propagate and receive these effects better. In addition, this study contributes to the academic discussion by showing evidence that the level of urban agglomeration is not the only factor that explains the capacity of a region to spill over its economic growth to its neighbors. Future analyses can delve deeper into the characteristics that make a canton more likely to generate or receive these spatial effects.

The remainder of the paper is structured in the following manner. Section 2 sets the spatial production function framework and the model selection strategy. Section 3 gives a detailed description of the variables used in the model including its spatial autocorrelation analysis. Section 4 estimates the spatial models under different spatial dependence structures. Section 5 focus on the results of the selected model and presents direct and indirect output elasticities estimates. Section 6 gives some concluding remarks.

2 Spatial Production Function Model

According to Bom, Ligthart (2014), the base approach that has been used to analyze the effects of public capital consists of a Cobb-Douglas production function, which considers labor (L), public (G) and private (K) capital stocks in a function as factors of a region i that, when interrelated by a technological factor A, determine the aggregate production level Y_i:

$$Y_i = A_i L_i^{\beta_1} K_i^{\beta_2} G_i^{\beta_3}, \quad i = 1, \ldots, n \tag{1}$$

One of the main assumptions of this function is that the effects of public capital are directly related to the stock of public capital. For this case, the parameter of interest is β_3, which represents the partial elasticity of public capital production. This equation can be transformed to its log linear form by applying natural logarithm in the equation, which is convenient to perform an econometric analysis. For simplicity and in accordance with a general practice in the literature, it is assumed that the technological factor is equal to 1, in order to eliminate the direct influence of technology on the production function. This allows us to focus on the effect of capital and labor inputs. The equation is presented as follows:

$$\ln(Y_i) = \beta_1 \ln(L_i) + \beta_2 \ln(K_i) + \beta_3 \ln(G_i) \tag{2}$$

The analysis of the contribution of production factors on the productivity and income level of nations has been widely studied around the world. The neoclassical tradition has proposed the use of aggregate production functions, such as the Cobb-Douglas function, that explain the contribution of the components that contribute to the country's aggregate product (technology, capital and labor), through the analysis of their respective elasticities. According to Dall'erba, Llamosas-Rosas (2015), this function continues to be one of the most used ways to estimate production factors and technological progress.

In contemporary research, there is an increasing emphasis on understanding the spatial or interregional effects of public capital on production (Foster et al. 2023, Marrocu, Paci 2010). A spatial approach for studying economics affairs in Ecuador have been developed in recent years (Guevara-Rosero et al. 2019, Munoz, Pontarollo 2016, Szeles, Muñoz 2016). Their main focus have been on convergence and agglomeration phenomena.

Looking forward on this path, this research is based on the new economic geography perspective which proposes that economic entities, be they families or businesses, are spread out across diverse spatial locations, inherently separated by distances. This spatial dispersion instills the economy with a unique spatial structure that cannot be overlooked. Interactions among these entities tend to evolve, get delayed, or even get constrained by the physical distances between them. Similarly, there can be indirect or spatial economic ripple effects which might spread differently based on the degree of interconnectedness of these entities within a particular spatial framework.

2.1 *Model selection*

Based on LeSage, Pace (2009), LeSage, Fischer (2008), López-Bazo et al. (1999), Florax, Folmer (1992), Anselin, Rey (1991), Elhorst (2010), Munoz, Pontarollo (2016) summarises a strategy to model selection, it uses a (robust) Lagrange Multiplier (LM), likelihood ratio (LR) and a Wald test.

Following this suggested strategy, a spatial lag model was selected:

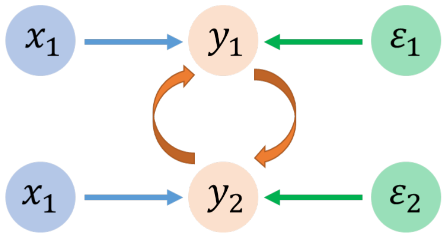


Figure 1: The spatial lag model for two regions. Straight lines represent non-spatial effects, curved lines are spatial effects

$$y = \rho W y + x\beta + \epsilon \tag{3}$$

where $y = \ln(Y)$ is a $n \times 1$ vector of observations of the dependent variable for n spatial units, ρ is the spatial autoregressive parameter which measures the intensity of the spatial interdependence, W is the $n \times n$ spatial weights matrix, β is a 3×1 coefficients vector of the covariates $\ln(L), \ln(K), \ln(G)$, and ϵ is the $n \times 1$ error term.

Figure 1 illustrates the spatial effects of two regions or spatial units in a spatial lag model. Golgher, Voss (2016) sets partial derivatives to study these effects (β_k coefficients represent the total effect of variable x_k):

$$S(W) = \begin{pmatrix} \frac{dy_1}{dx_{1k}} & \cdots & \frac{dy_1}{dx_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{dy_n}{dx_{1k}} & \cdots & \frac{dy_n}{dx_{nk}} \end{pmatrix} = \beta_k (I - \rho W)^{-1} \tag{4}$$

where $S(W)_{11} = \frac{dy_1}{dx_{1k}}$ is the effect of x_k from region 1 over y of the same region and $S(W)_{n1} = \frac{dy_n}{dx_{1k}}$ is the effect of x_k from region 1 over y of region n. For a given covariate x_k, these let us define the average direct, total and indirect impacts:

$$\bar{M}_{\text{direct}} = n^{-1} \text{tr}(S(w) \tag{5}$$

$$\bar{M}_{\text{total}} = n^{-1} \iota_n^{-1} S(w) \iota_n \tag{6}$$

$$\bar{M}_{\text{indirect}} = \bar{M}_{\text{total}} - \bar{M}_{\text{direct}} \tag{7}$$

where ι_n is a $n \times 1$ vector of ones, $\bar{M}$ is the average effect.

Five spatial weights matrices W are applied with the chosen model. Contiguity matrices mark the elements of W with a dichotomous variable equal to 1 when the spatial units i and j are neighbors of each other and 0 otherwise. A knn-matrix based on a number k of nearest neighbors marks with 1 those regions that are within the k closest to each other. Specifically, we set three knn-matrices where $k = 5, 10$ and $k = 215$ (the total number of cantons minus 1). The inverse distance matrix W consists of dividing 1 for the distance weighting defined by the researcher. In this case, the greater the distance, the lower the weight assigned between regions.

3 Exploratory Spatial Data Analysis

3.1 The data

This study uses various public data sources to determine the dependent and independent variables for spatial regression analysis. Every data point in the dataset represents variables from 216 cantons within mainland Ecuador. Cantons without clear boundaries and those situated in the Galapagos Islands were not considered. Every canton is labeled using its unique code as per the National Institute of Statistics and Censuses (INEC) system.

Table 1: Data summary statistics. Per-capita values are shown in parentheses.

Statistic	**NOGVA**	**Public**	**Private**	**WAP**	**Pop.**
Min	5.20mn (858.4)	20,000 (0.88)	400 (0.015)	1,499	2,455
Q1	26.59mn (1,764.7)	668,148 (31.30)	2,820 (0.17)	8,848	13,085
Median	58.69mn (2,496.8)	1,632,026 (65.27)	31,320 (0.77)	18.760	28,080
Mean	421.50mn (3,155.4)	5,504,143 (93.49)	7,291,445 (19.52)	54,127	77,199
Q3	193.80mn (3,497.8)	4,679,626 (104.22)	565,097 (8.28)	39,856	60,519
Max	24.43mn (32,627.6)	183,876,079 (1,079.49)	539,377,575 (671.32)	1,943,861	2,644,891

Notes: "mn" … million, "Pop." … Population.

The geospatial data for the cantons was sourced from the Military Geographic Institute's (IGM) spatial database, which details Ecuador's territorial organization by cantons. This data was integrated into the primary database and employed to compute the spatial weight matrices for the model.

Table 1 shows summary statistics of the variables from year 2017 used in the study: non-oil gross value added (NOGVA), private investment (Private), public investment (Public), working age population (WAP) and population. Their per capita values are shown in parenthesis. We next provide a more in-depth explanation of the variables employed in the econometric modeling.

Production The non-oil gross value added variable is used, in per-capita terms for the year 2017 in US dollars ($NOGVApc$), obtained from the provisional regional accounts of the Central Bank of Ecuador as a proxy for production at the canton level. This variable was transformed into per-capita values with the population information from INEC. Figure 2a presents the spatial concentration of production in cantons: non-oil gross value added.

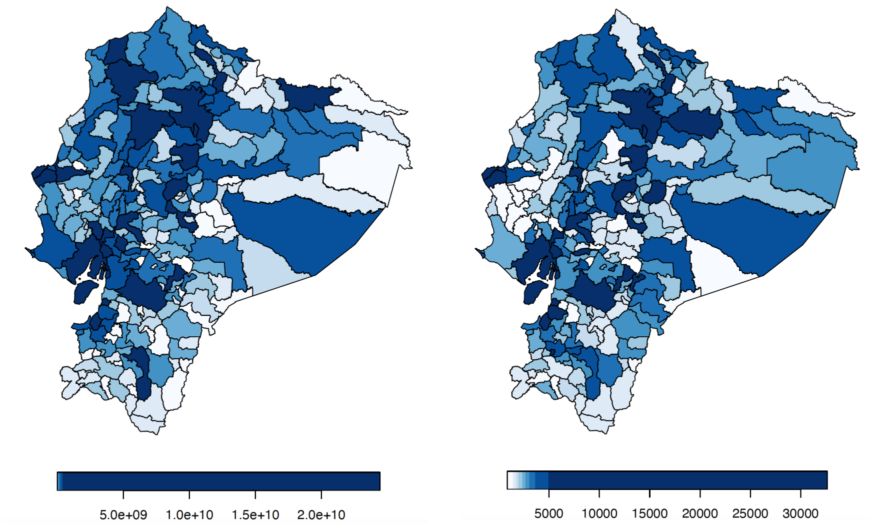
Public Capital Blades, Meyer-zu Schlochtern (1997) note that when it comes to specifying capital in productivity research, two main approaches are predominantly used:

- When available in national accounts, the capital stock (CS) is used, signifying the capital assets' value within the economy. The gross capital stock (GCS) method values assets based on their acquisition time, ideal for calculating the total anticipated returns from assets over their lifespan. Yet, when gauging value-added changes for a single year, it is limited because it factors in projected income for the asset's entire useful life, both before and after the specified year. Conversely, the net capital stock (NCS) method omits projected income from years prior to the one under scrutiny but includes future anticipated earnings. The underlying rationale for these stock methods is the belief that capital services are aligned with its cost. Nevertheless, they overlook the fact that assets have diverse lifespans, meaning their production impact may vary within a particular year.

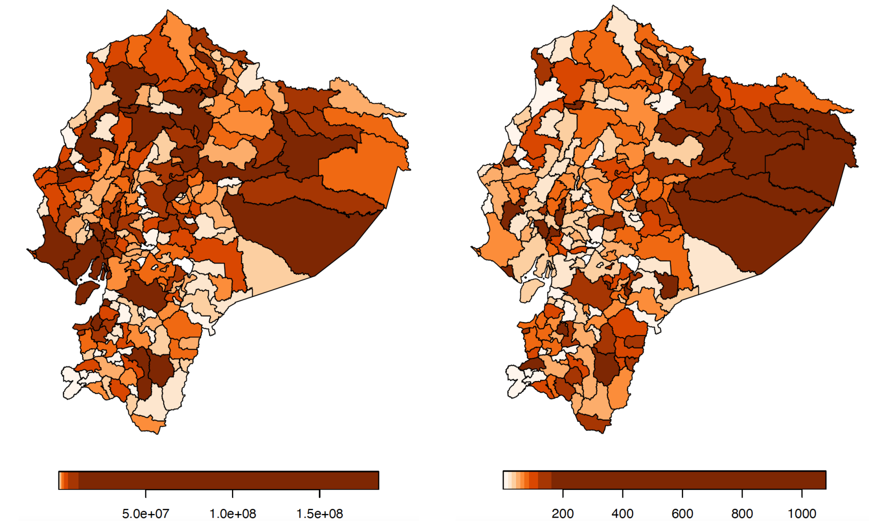
- Capital consumption (CC) over a specified timeframe serves as a proxy for discerning the capital contribution to the production function, especially for assets with diverse lifespans and years in operation. A notable downside is the inclusion of CC in production metrics like gross domestic product (GDP) or gross value added (GVA). Yet, these averages remain unaffected by capital consumption. This is because CC embodies the value that is subtracted to preserve the asset owner's wealth. Consequently, the author contends that annual fluctuations in GDP or GVA are not influenced by the CC.

Blades, Meyer-zu Schlochtern (1997) state that employing CC variables yields superior results compared to CS when analyzing Total Factor Production for the OECD, using 1999 data. This is attributed to the fact that the CC variable offers a more comprehensive insight into the growth of added value stemming from the capital factor's contribution.

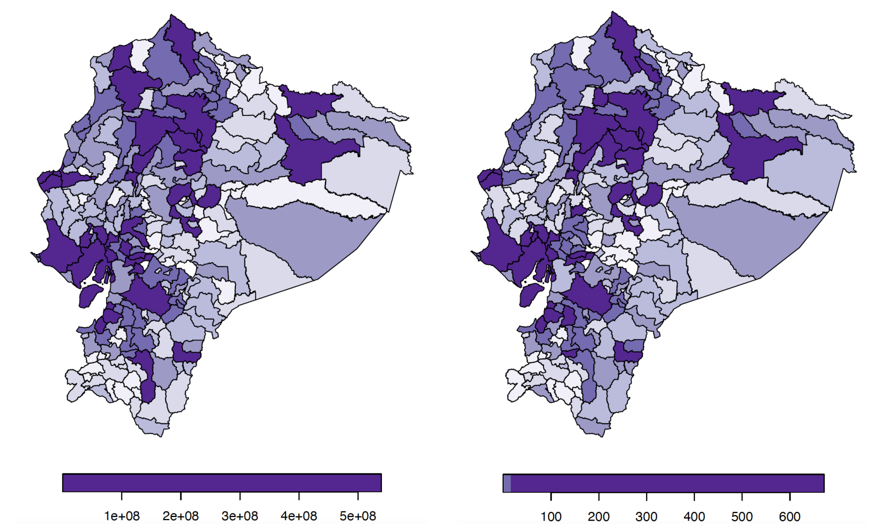
For Ecuador, cantonal-level data for CS or CC variables, like the gross fixed capital formation (GFCF) related to public capital, is absent. Consequently, in alignment with



(a) Non-oil gross value added (left panel) and per-capita values (right panel)



(b) Public capital (left panel) and per-capita values (right panel)



(c) Private capital (left panel) and per-capita values (right panel)

Figure 2: Spatial distributions (Choropleth maps) of main variables

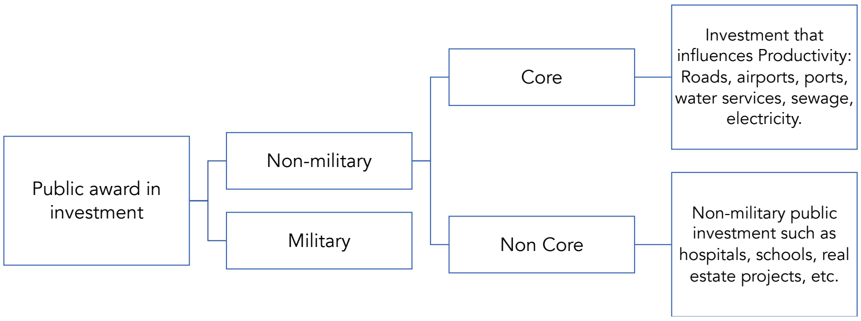


Figure 3: Public investment classification

employing a CC-based approach as a proxy for public capital, data from the National Public Procurement Service (SERCOP in Spanish) from 2017 is used.

The data entries in this source are recorded at the process level of contracting. However, they do not include variables specifying the canton where the work takes place. Yet, each data point has an identifier for the contracting entity responsible for the award, and this identifier includes the Entity's RUC (Unique Registry of Taxpayers).

In an effort to identify the location of various projects, a variable was created using the RUC of the awarding public entities. These recorded work data points were then matched with the Fiscal Administration (SRI in Ecuador) RUC database, which provides information about the canton where each entity is based. This merge resulted in an intermediate dataset detailing awarded contracts along with the respective canton of each entity. However, this dataset only indicates the location of the contracting entity and not necessarily the exact canton where the work occurs. This distinction is particularly important for contracting entities that invest in multiple cantons beyond their primary location. This is especially true for entities like the Decentralized Autonomous Governments at both national and provincial levels and regional electrical companies. To illustrate, the Decentralized Autonomous Government of Azuay, headquartered in the provincial capital of Cuenca, oversees projects not just in Cuenca but in other cantons within that province. Given this complexity, a meticulous case-by-case review was essential to accurately assign the correct canton to each contracting process. This involved in-depth analysis of individual contracting processes to pinpoint the specific canton for each investment. Nonetheless, for Decentralized Autonomous Governments at the cantonal and parish levels, and their public corporations, such scrutiny was not required. Their projects are typically located in the same canton as the entity's main office.

Furthermore, in line with existing literature, these projects were categorized as either non-military or military and also delineated between core and non-core (Figure 3)

In the final step, the data pertaining to the amounts awarded by canton were incorporated, with a focus on exclusively including those related to core public capital projects. This process resulted in the creation of a variable containing the award amounts for core public works, organized by canton and expressed in US dollars. It is transformed into per capita terms using the INEC population projection for the year 2017, which was prepared with data from the 2010 census, calling this variable $PubCpc$ which canton concentration is shown in Figure 2b.

Private Capital To represent private capital, data on corporate capital expenditures from the Superintendency of Companies of Ecuador were utilized. This data, available at the canton level, was then aggregated per canton and converted into per capita terms (PrivCpc). Canton concentration is shown in Figure 2c.

Labor For the effects of labor's role within the Cobb-Douglas function, and to align it in US dollar terms like the other variables, the method proposed by Han et al. (2016) was adopted. This method equates labor to the Economic Working Age Population (WAP). To achieve this, population projections from the 2010 census were utilized. These

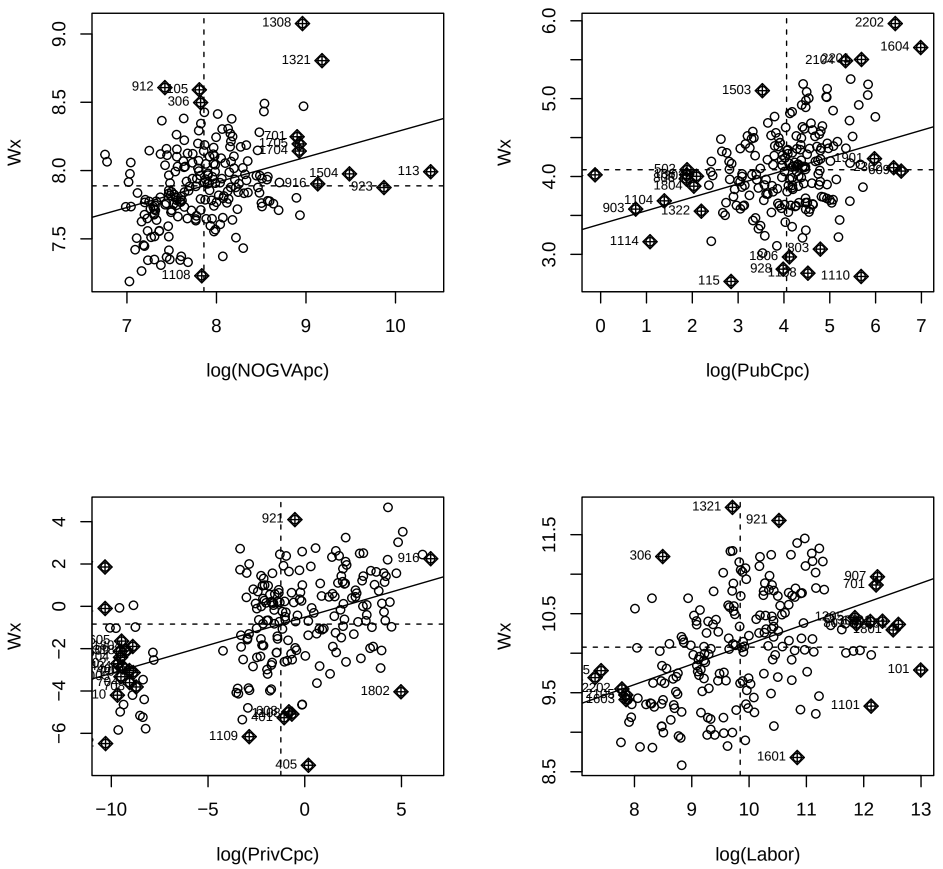


Figure 4: Moran plot for the logarithms of non-oil gross value added (NOGVApc), public capital per capita (PubCpc), private capital per capita (PrivCpc) and labor.

projections are sorted by canton and age. Subsequently, data from each canton regarding the population aged 15 and above was aggregated, aligning with the WAP definition.

3.2 Spatial Autocorrelation

Moran's I test is utilized in order to test for spatial dependency. The assessment is based on a hypothesis that is a random spatial distribution of the observations. If the null hypothesis is rejected, it suggests that there is a discernible spatial pattern or structure embedded within the data.

Figure 4 shows positive Moran's I for the logarithms of non-oil gross value added (NOGVApc), public capital per capita (PubCpc), private capital per capita (PrivCpc) and labor. They are all significant at 5% which is confirmed in Table 2. They suggest underlying spatial dependence in all variables. The Moran plot's first and third quadrants (high-high, HH, and low-low, LL) display cantons that are neighbored by other cantons with similar values, whether consistently high (in the case of HH) or consistently low (for LL). The second and fourth quadrants of the Moran plot, namely low-high (LH) and high-low (HL), exhibit cantons where a low (or high) value of the variable is neighbored by cantons with high (or low) values of the same variable. Cantons are present in all quadrants of Figure 4. Quadrants I and III have over 60% of cantons which explains positive slopes.

Table 2 presents the Moran's I statistic (MI), its expected value (E[MI]), variance (V[MI]), z-value and p-value under different approaches for variance computation: Randomization, Normal and Monte Carlo. Z-value let us compare across these setups. In the

Table 2: Moran's I test for the logarithms of non-oil gross value added (NOGVApc), public capital per capita (PubCpc), private capital per capita (PrivCpc) and labor.

	log(NOGVApc)			log(PubCpc)		
	Rnd.	**Normal**	**MC**	**Rnd.**	**Normal**	**MC**
MI[a]	0.2087	0.2087	0.2087	0.1662	0.1662	0.1662
E[MI][b]	-0.0047	-0.0047	-0.0042	-0.0047	-0.0047	-0.0041
V[MI][c]	0.0018	0.0018	0.0020	0.0018	0.0018	0.0020
z-value	4.9898	4.9645	4.7512	3.9911	3.9772	3.8430
p-value	0.0000	0.0000	0.0010	0.0000	0.0000	0.0010

	log(PrivCpc)			log(Labor)		
	Rnd.	**Normal**	**MC**	**Rnd.**	**Normal**	**MC**
MI[a]	0.2850	0.2850	0.2850	0.2622	0.2622	0.2622
E[MI][b]	-0.0047	-0.0047	-0.0041	-0.0047	-0.0047	-0.0049
V[MI][c]	0.0018	0.0018	0.0017	0.0018	0.0018	0.0018
z-value	6.7409	6.7415	6.9179	6.2241	6.2100	6.3173
p-value	0.0000	0.0000	0.0010	0.0000	0.0000	0.0010

Notes: [a]Moran's I Statistic; [b]Expected Moran's I; [c]Moran's I variance; "Rnd.": Randomization; "MC": Monte Carlo.

case of non-Oil gross value added (NOGVApc) and public capital per capita (PubCpc), Moran's I is greatest under randomization (4.9898 and 3.9911 respectively). For private capital per capita (PrivCpc) and labor, Moran's I is greatest in Monte Carlo (6.9179 and 6.3173 respectively). All results implies that there is evidence of robust positive spatial autocorrelation at 5% significance level in all cases.

4 Spatial Model choice

As mentioned in Section 2.1, Lagrange multiplier (LM), likelihood ratio (LR) and a Wald test are used to select the spatial lag model. Table 3 presents both the LM test statistics and the robust LM test statistics, specifically for a spatial lag in the dependent variable and for a spatial error term. Accompanying these statistics are the respective p-values. Versions that are not robust show significant p-values but robust counterparts do not.

Testing with different spatial matrices allows researchers to study spatial sensitivity. Each type of matrix captures a distinct notion of spatial interaction—for example, contiguity matrices focus on neighboring units, while distance-based matrices emphasize proximity, and k-nearest neighbor matrices ensure each unit is connected to a fixed number of others. By examining results across different spatial weight specifications, analysts can assess whether spatial dependence remains consistent under varying definitions of spatial proximity (Anselin, Rey 1991). In our case, spatial sensitivity to changes in spatial weights is examined through two approaches: Lagrange Multiplier Tests and the estimation of the SLM coefficients.

Table 3 outlines different weights matrices. Contiguity weight matrix is a standard base approach, *knn* distance matrices (*knn* 5, 10, 215) let us examine the robustness of the estimation as more neighbors are included. Inverse distance let us check the behavior of model estimation *inverting* the weights as distance is greater. It is worth noting that, for regularity conditions, all weights are row-normalized. These results exhibit a clear pattern: spatial weights matrices that emphasize closer relationships yield significant p-values, while those representing broader or more distant spatial interactions tend to produce insignificant p-values as the spatial range increases.

Traditional LM tests, considering all contiguity and *knn* (up to k=10) spatial weights matrices, show consistent results in the sense that they reject the hypothesis of no spatially lagged-dependent variable at a 5% significance level. However, robust LM tests the hypothesis of no spatially autocorrelated error is not rejected for any spatial weights matrix. As illustrated in Figure 2 of Putra et al. (2020), when the Robust LM test is not significant, no clear decision can be made. In this case, the LR and Wald tests can assist in determining the appropriate model.

Table 3: Lagrange multiplier tests for a spatially lagged-dependent variable and spatial error correlation.

	LMlag		RLMlag		LMerr		RLMerr	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Contiguity	13.977	0.000	0.635	0.426	14.084	0.000	0.742	0.389
knn 5	12.357	0.000	0.036	0.850	14.788	0.000	2.467	0.116
knn 10	4.346	0.037	0.235	0.628	6.887	0.009	2.776	0.096
knn 215	0.502	0.478	0.000	1.000	0.502	0.478	0.000	1.000
Inverse distance	1.385	0.239	0.236	0.627	2.320	0.128	1.170	0.279

Table 4: p-values from likelihood ratio (LR) and a Wald test. Columns SDM, SLM and SEM show LR of row and column comparison

p-values	SDM	SLM	SEM	Wald	LR
SAC[a]	0.8175	0.6794	0.9041	0.7246	0.0141
SDM[b]		0.7101	0.8335	0.0001	0.0003
SLM[c]			-	0.0002	0.0004
SEM[d]				0.0001	0.0003

Notes: [a]Spatial autoregressive model; [b]Spatial Durbin model; [c]Spatial lag model; [d]Spatial error model.

Table 4 present p-values from LR and Wald tests in the last two columns. The null hypothesis in these cases is the absence of spatial dependence, the hypothesis is rejected in almost all models except in SAC for Wald test. The first three columns in Table 4 show LR p-values of row-column model specifications: spatial autoregressive model (SAC), spatial Durbin model (SDM), spatial lag model (SLM) and spatial error model (SEM). For example, 0.7101 is the LR test p-value of comparing SDM and SLM. This table shows there is no difference, it reduces our model specification to SLM and SEM based on the parsimony principle.

Although the SEM model considers spatial dependence in the disturbance process, it does not offer insights into spillovers (Elhorst, Vega 2013). As our goal is to investigate the impact of public capital spillovers on gross value added, and the available evidence supports the use of spatial lag model (SLM), it is the preferred method over spatial error model (SEM).

5 Results

5.1 *Estimation and Impacts*

We examine if the production level of a canton can impact the corresponding variable in its adjacent cantons. Estimation results of SLM (spatial lag model) are presented in Table 5. There are 6 models depending on the spatial weights specification: (0) ordinary least squares-OLS (1) geographical contiguity, (2) k-nearest neighbors with $k = 5$, (3) k-nearest neighbors with $k = 10$, (4) k-nearest neighbors with $k = 215$, and (5) inverse distance.

In linear regressions, including spatial linear regressions, conclusions about the significance of the coefficients can be misleading in the presence of multicollinearity (Corrado, Fingleton 2012). Based on Morales-Oñate, Morales-Oñate (2023), a multicollinearity test was performed in OLS model finding that the multicollinearity hypothesis is rejected at 5% significance for all variables.

The findings indicate a positive spatial correlation among the production levels (GVA) of various cantons in Ecuador. This is evident in the significant ρ value observed for the contiguity and neighborhood matrices up to closest 10. However, this is not the case for other spatial weights specifications.

Based on Kubara, Kopczewska (2024), it was determined that setting $k = 4$ optimizes the Akaike information criterion (AIC), yielding a value of $AIC = 291.5433$. Furthermore, the study suggests that fine-tuning W by adjusting a few spatial units (such as changing knn from 5 to 4) result in negligible gains, consistent with our findings. Among

Table 5: Estimation results in spatial lag model.

	OLS (Model (0))		**Contiguity** (Model (1))		**knn 5** (Model (2))	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
(Intercept)	6.356	0.000	3.959	0.000	3.883	0.000
log(PubCpc)	0.099	0.002	0.094	0.002	0.093	0.002
log(PrivCpc)	0.036	0.000	0.031	0.001	0.036	0.000
log(Labor)	0.117	0.000	0.109	0.000	0.106	0.001
ρ			0.315	0.000	0.330	0.001
Log-likelihood	-146.7143		-140.3441		-140.703	
AIC	301.4286		292.6883		293.4061	

	knn 10 (Model (3))		**knn 215** (Model (4))		**Inverse distance** (Model (5))	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
(Intercept)	4.344	0.000	14.219	0.199	2.198	0.304
log(PubCpc)	0.098	0.002	0.098	0.002	0.097	0.002
log(PrivCpc)	0.035	0.000	0.036	0.000	0.036	0.000
log(Labor)	0.112	0.000	0.116	0.000	0.113	0.000
ρ	0.262	0.047	-0.998	0.246	0.211	0.211
Log-likelihood	-144.7379		-146.0412		-145.9331	
AIC	301.4759		304.0823		303.8663	

all *knn* distance matrices in Table 5, *knn* 5 emerges as the optimal. Following the AIC criteria, the contiguity matrix has the lowest AIC overall. In accordance with the AIC criteria, the contiguity matrix exhibits the lowest AIC overall.

If we were to base our selection solely on the specification of W, the contiguity matrix would be the preferred option. However, our objective is to present all possible scenarios whenever feasible. The analysis compares different spatial weight matrices to test the robustness of SLM and assess how various spatial structures affect estimated spatial effects. Although the contiguity matrix was used for the main analysis, k-nearest neighbors (k=5,10,215) and inverse distance matrices helped validate the results. The consistency of spatial lag coefficients and p-values across different matrices confirmed the stability of the findings (LeSage, Pace 2009). This comparison enhances model credibility and contributes to refining spatial weight matrix selection in future research.

When working with a geographically incomplete dataset, the concept of contiguity might not be suitable. In our case, four insular cantons and two cantons from Guayas (General Antonio Elizalde) and Manabi (Junin) were removed due to lack of information. In Continental Ecuador, we work with 99.08% of cantons. Therefore, we can reasonably assume our dataset as complete.

The estimates of Model (3) are slightly higher than the coefficients in Models (1) and (2), coefficients of Model (0) are the highest. Estimated coefficients of public, private and labor variables are significant at 5% in almost all cases. ρ in Model (1) and Model (2) are significant, large and similar, it decreases and loses significance in the rest of the models. It is not appropriate to compare the coefficient estimates of spatial models to OLS, as the coefficient estimates in spatial models exclusively capture the direct marginal effects. We obtain mean direct effects, mean indirect effects, and total effects for comparison purposes. It is worth noting that ρ decreases as distance grow. This is consistent with ρ which is not significant in the inverse distance spatial weights specification.

Upon identifying evidence of an indirect spatial effect between the production levels of the cantons, our focus shifted to quantifying the influence exerted by the production factors via this transmission mechanism. Table 6 showcases the direct and indirect output elasticity calculations, which are derived from the coefficient estimates found in Table 5.

Utilizing the S matrix in equation (4), we discovered significant evidence supporting these indirect effects. Specifically, the average indirect effect of public capital, when evaluated with contiguity, stands at 13.69% with significance level at 5%. In comparison, private capital manifests a slightly more pronounced impact at 4.12%, and labor displays the most substantial indirect effect, measuring 4.77%. Similar results are obtained for distance up to five neighbors. However, significance of indirect impacts is lost in the rest

Table 6: Direct and indirect output elasticity estimates.

	Contiguity (Model (1))		**knn 5** (Model (2))		**knn 10** (Model (3))		**knn 215** (Model (4))		**Inv. dist.** (Model (5))	
	Est.	**p-val.**	**Est.**	**p-val.**	**Est.**	**p-val.**	**Est.**	**p-val.**	**Est.**	**p-val.**
log(PubCpc)										
Total	0.1369	0.0033	0.1388	0.0046	0.1330	0.0071	0.0027	0.6015	0.2091	0.3832
Direct	0.0958	0.0016	0.0949	0.0023	0.0989	0.0017	0.0984	0.0010	0.0979	0.0018
Indirect	0.0412	0.0478	0.0439	0.0484	0.0342	0.1674	-0.0958	0.8371	0.1111	0.5434
log(PrivCpc)										
Total	0.0453	0.0015	0.0532	0.0004	0.0478	0.0014	0.0010	0.5988	0.0764	0.3984
Direct	0.0317	0.0007	0.0364	0.0002	0.0356	0.0003	0.0355	0.0003	0.0358	0.0002
Indirect	0.0136	0.0362	0.0168	0.0218	0.0123	0.1331	-0.0346	0.8307	0.0406	0.5588
log(Labor)										
Total	0.1586	0.0010	0.1588	0.0016	0.1519	0.0023	0.0031	0.5951	0.2421	0.3648
Direct	0.1109	0.0003	0.1086	0.0008	0.1129	0.0006	0.1164	0.0005	0.1134	0.0005
Indirect	0.0477	0.0353	0.0503	0.0306	0.0390	0.1331	-0.1133	0.8351	0.1287	0.5337

Notes: "Est.": Estimate; "p-val.": p-value; "Inv. dist.": Inverse distance.

of spatial weights matrix specifications.

Taking into account the total effect of public capital on economic performance in Model (1), which is 0.045, and breaking it down into its components (direct: 0.0317 and indirect: 0.0136), we find that the spatial (indirect) component accounts for 30% of the overall impact. Meanwhile, the direct effect contributes the remaining 70%. To determine the feedback effects of each factor input, we subtract the coefficient estimates from the direct output elasticity estimates. For example, in the case of public capital, the feedback effect is $0.0958 - 0.094 = 0.002$. This means that each canton exerts a feedback effect of 0.002 on its neighboring cantons, which in turn influences their neighbors, creating a ripple effect throughout the network. For private capital and labor, the feedback effect is 0.001 and 0.002 respectively.

The findings suggest that public capital, along with other production factors, produces spatial impacts among adjacent cantons. This chain of influence stems from how these factors affect external production levels, which subsequently shape the production levels of neighboring spatial entities.

5.2 *Marginal effects by cantons*

In subsection 5.1, direct, indirect and total effects were computed and analyzed. These measures give us valuable average information. However, the average indirect effects fail to convey the spillover impacts of individual canton on one another. Fixing the estimated public capital coefficient $\beta = 0.0938$ in equation (4), generates a $S(W)$ matrix of size $n \times n$ whose elements let us capture these individual canton spillovers. A unit increment of public capital in canton i has an individual direct effect on production of the same canton i (diagonal of $S(W)$). Also, a unit increment of public capital in canton i has an individual indirect effect on production of canton j (off-diagonal of $S(W)$). We are interested in the row and column sums of the off-diagonal elements of $S(W)$, $i \neq j$ which are called row effects and column effects respectively.

Leveraging the spatial contiguity weights matrix and fixing the estimated public capital coefficient in equation (4), we delve into the spatial impacts of public capital on individual cantons. We dissect both the row and column effects to determine which spatial units exert the most influence over their adjacent counterparts (column effects: total spillover effects of a specific canton onto the production of other cantons) and identify which units are more reliant on their neighboring regions (row effects: when all other cantons increase public capital input by one unit, row effects are spillover effects from other cantons to a specific canton). Figure 6, Table 7 and Table 8 show these effects.

The findings highlight that the Cañar canton is the preeminent canton in the country that positively impacts its neighbors through public investment. It is crucial to note that this canton has two unique interior neighbors, which exclusively share a border with Cañar (see Figure 5). Among Suscal, Cañar and El Tambo, Cañar has 28% of gross

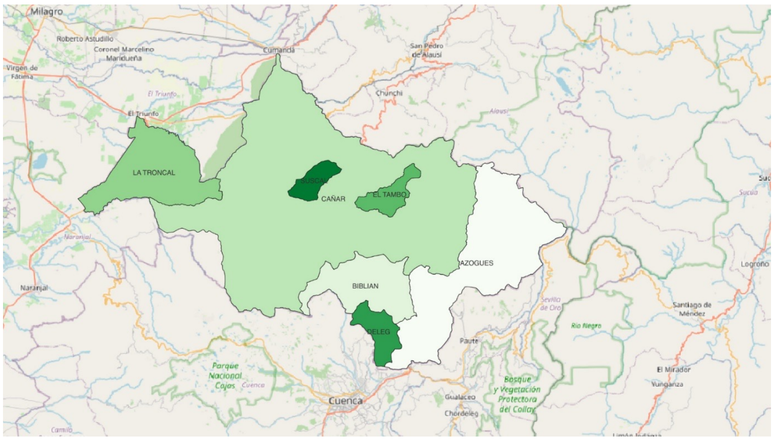


Figure 5: Cañar

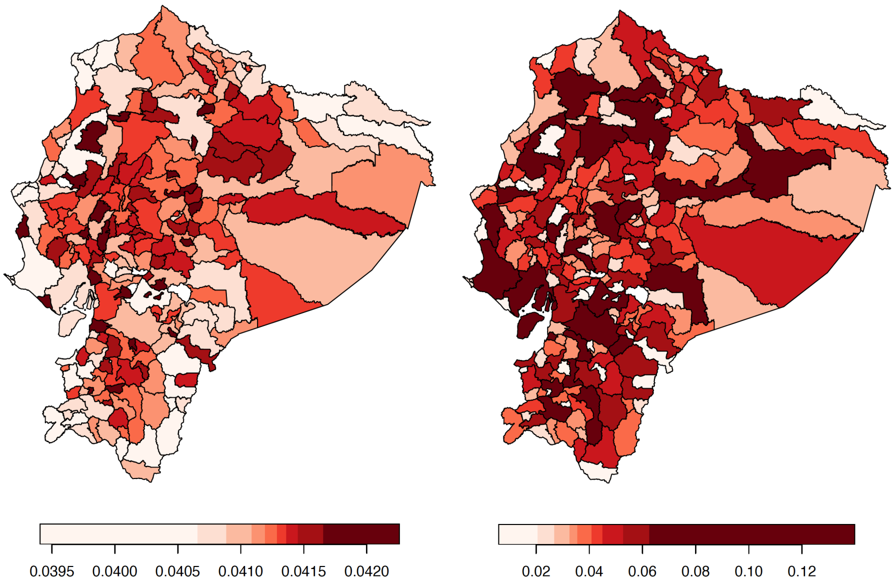


Figure 6: Public's capital row (left) and column (right) effects on per capita non-oil gross value added

value added (GVA), 23% of public capital and 79% of the population. This suggests that it preeminent column effect is influenced by a population effect. Ecuador's major cities – Quito, Cuenca, and Guayaquil – belong to the primary top 10 cantons where public investment significantly affects surrounding areas. Nonetheless, Table 7 also presents ranked population size and GVA, which seem not to be decisive factors in determining the observed impact of public investment since their log-scale Pearson correlation with column effects are 0.37 and 0.40, respectively. Spatial structure play a significant role in this regard since the contiguity weight matrix indicates that 60% of Ecuador's cantons have five to 12 neighbors.

Column effects in Table 7 can be interpreted as follows. On average, an increase of one percentage point in public capital in the Santa Elena canton increases the economic performance (measured in terms in GVA) of its surrounding cantons by 0.1036%.

On the other hand, Table 8 (row effects) show the cantons that benefit most from the public investment of their neighbors, which are Tambo and Suscal. They are completely surrounded by the Cañar canton, which generates the greatest column effect. Row effects in Table 8 can be interpreted as follows. In the case of the Rumiñahui canton, on average, an increase of one percentage point in public capital in its surrounding cantons increases its economic performance by 0.0419%.

Table 7: Public's capital column effects on per-capita non-oil gross value added.

Column effect Rank	Value	GVA Rank	Value	Population Rank	Value	Canton Code	Canton	Province
1	0.1398	55	192,390,383	49	66,996	303	CAÑAR	CAÑAR
2	0.1053	144	36,163,641	122	24,017	1109	PALTAS	LOJA
3	0.1036	27	417,373,082	17	176,373	2401	SANTA ELENA	SANTA ELENA
4	0.1020	1	24,426,597,900	2	2,644,145	1701	D.M. QUITO	PICHINCHA
5	0.0973	35	314,327,442	21	131,877	1303	CHONE	MANABI
6	0.0952	3	4,392,835,893	3	603,269	101	CUENCA	AZUAY
7	0.0921	2	20,554,798,446	1	2,644,891	901	GUAYAQUIL	GUAYAS
8	0.0874	16	905,261,666	18	171,038	1201	BABAHOYO	LOS RIOS
9	0.0838	42	255,159,287	45	74,158	1501	TENA	NAPO
10	0.0788	20	655,491,210	20	140,670	804	QUININDE	ESMERALDAS

Table 8: Public's capital row effects on per-capita non-oil gross value added.

Row effect Rank	Value	GVA Rank	Value	Population Rank	Value	Canton Code	Canton	Province
1	0.0423	113	56,500,676	168	11,673	305	EL TAMBO	CAÑAR
2	0.0423	186	15,269,624	200	6,128	307	SUSCAL	CAÑAR
3	0.0421	78	108,585,168	61	54,308	921	PLAYAS	GUAYAS
4	0.0420	130	44,499,752	116	24,615	1305	FLAVIO ALFARO	MANABI
5	0.0420	153	30,696,591	164	12,982	605	CHUNCHI	CHIMBO-RAZO
6	0.0419	18	803,979,272	25	107,043	1705	RUMIÑAHUI	PICHINCHA
7	0.0419	107	59,324,110	115	24,777	903	BALAO	GUAYAS
8	0.0419	141	41,454,460	126	23,689	1319	PUERTO LOPEZ	MANABI
9	0.0418	73	121,913,902	68	50,241	2302	LA CONCORDIA	S.T. DE LOS TSACHILAS
10	0.0418	9	1,484,310,229	7	293,005	907	DURAN	GUAYAS

It is interesting that in the lists of the main cantons there are several satellite cities, such as Rumiñahui, which borders the Metropolitan District of Quito and Durán with Guayaquil.

The large cities in Ecuador, such as Quito and Guayaquil, concentrate a large part of the country's economic activity, and the surrounding cantons are usually home to workers and companies that interact with these economic centers and benefit from their economic dynamism. Therefore, an increase in the economic activity of these cities linked to public capital investments can have a significant influence on the surrounding cantons.

However, it can be argued that the political-administrative power of these cities can also influence the economic performance of the surrounding regions. Therefore, it should be considered that in Ecuador each of these regions has legal autonomy over its competencies, therefore, when analyzing regions with the same level of hierarchy (cantons) there can be no inference in the political decision making of larger cantons. Additionally, although Quito and Guayaquil are considered metropolitan districts in Ecuador, they do not contain other municipalities or cantons within them, as is the case with most metropolitan districts worldwide.

There are several mechanisms for the transmission of spillover effects of public capital between cantons. As explained by Berndt, Hansson (1992), public capital can reduce firms' production costs, improving their output and performance. This in turn motivates firms to demand goods, services and labor from neighboring cantons, thereby increasing household production and consumption.

This increase in productivity can also encourage the formation of industrial clusters. These clusters can expand to neighboring cantons, as has been the case of Rumiñahui, which is a satellite canton of Quito, or Durán, which is located near Guayaquil.

In addition to these causes, investment in connectivity infrastructure can improve access to services in neighboring cantons, as well as boost trade and labor mobility, which impacts production in neighboring cantons.

6 Conclusions

Similar to the literature found on developed countries, this research has found evidence of public capital spillover effects in Ecuador. To the best of our knowledge, there are no clear studies differentiating between public and private (capital) spillovers on developing countries including Ecuador. Our work can give a guidance to follow a similar path in information gathering about public capital, exploring spatial structures and elasticity analysis to be explored in future research.

The findings indicate that in Ecuador, production factors, especially public capital, establish spatial relationships among the cantons. This primarily transmission mechanism is through the production levels within the cantons themselves. The SLM model evaluated with a contiguity matrix shows that the spatial effects of public capital (0.012) can explain 30% of the total effect that this factor has on the economic performance of the cantons. In contrast, the non-spatial or direct influence (0.032) represents 70%. Given its significance in the total impact, the spatial structure in the model is essential, suggesting that it is not feasible to assume independence among the cantons under study.

Although the SLM model indicates that the most populous cities in Ecuador have the most substantial direct and indirect effects on their neighboring cantons, there are also smaller cities, both in terms of population and economic significance, that play a role in this dynamic.

In addition, this study contributes to the academic discussion by showing evidence that the level of urban agglomeration is not the only factor that explains the capacity of a region to spill over its economic growth to its neighbors. By taking a more detailed sample of regions, a more specific analysis of the possible economic and spatial dynamics that arise between them should be carried out.

The findings have important implications for shaping public policies, especially those directed at promoting regional growth and development. These implications arise from the ability to direct investments preferentially towards cantons that demonstrate a more significant regional ripple effect. Nevertheless, any policy formulation should also consider the temporal dynamics of these effects to ensure enduring and equitable growth across regions.

Future research could delve into the longitudinal variation of these effects, probing how they evolve over extended periods. Additionally, a more granular examination could be undertaken to discern the specific attributes that lead certain cantons to exert a more pronounced contagion influence, as well as to identify which cantons derive the most significant benefits from these ripple effects.

References

Álvarez IC, Barbero J, Zofío JL (2016) A spatial autoregressive panel model to analyze road network spillovers on production. *Transportation Research Part A: Policy and Practice* 93: 83–92. CrossRef.

Anselin L, Rey S (1991) Properties of tests for spatial dependence in linear regression models. *Geographical analysis* 23[2]: 112–131. CrossRef.

Aschauer DA (1989) Is public expenditure productive? *Journal of monetary economics* 23[2]: 177–200. CrossRef.

Berndt ER, Hansson B (1992) Measuring the contribution of public infrastructure capital in Sweden. *The Scandinavian Journal of Economics* 94: 151–168. CrossRef.

Blades D, Meyer-zu Schlochtern J (1997) How should capital be represented in studies of total factor productivity. Canberra group on capital stock statistics, OECD, https://www.oecd.org/sdd/na/canberragrouponcapitalstockstatistics-march1997.htm

Bom PR, Ligthart JE (2014) What have we learned from three decades of research on the productivity of public capital? *Journal of economic surveys* 28[5]: 889–916. CrossRef.

Briones Bendoza XF, Molero Oliva LE, Zamora OX (2018) The production function Cobb-Douglas in Ecuador. *Tendencias* 19[2]: 45–73. CrossRef.

Corrado L, Fingleton B (2012) Where is the economics in spatial econometrics? *Journal of Regional Science* 52[2]: 210–239

Dall'erba S, Llamosas-Rosas I (2015) The impact of private, public and human capital on the US states economies: Theory, extensions and evidence. *Handbook of research methods and applications in economic geography*: 436–467. CrossRef.

Elhorst JP (2010) Applied spatial econometrics: Raising the bar. *Spatial economic analysis* 5[1]: 9–28. CrossRef.

Elhorst P, Vega SH (2013) On spatial econometric models, spillover effects, and W. 53rd congress of the European Regional Science Association, Palermo, Italy, http://hdl.handle.net/10419/123888

Fingleton B (2001) Equilibrium and economic growth: Spatial econometric models and simulations. *Journal of regional Science* 41[1]: 117–147. CrossRef.

Florax R, Folmer H (1992) Specification and estimation of spatial linear regression models: Monte Carlo evaluation of pre-test estimators. *Regional science and urban economics* 22[3]: 405–432. CrossRef.

Foster V, Gorgulu N, Straub S, Vagliasindi M (2023) The impact of infrastructure on development outcomes: A qualitative review of four decades of literature. Policy Research Working Papers, 10343, World Bank, http://hdl.handle.net/10986/39515

Golgher AB, Voss PR (2016) How to interpret the coefficients of spatial models: Spillovers, direct and indirect effects. *Spatial Demography* 4: 175–205. CrossRef.

Guevara C (2016) Growth agglomeration effects in spatially interdependent Latin American regions. *Journal of Applied Economic Sciences* 11[45]: 1350–1355

Guevara-Rosero GC, Riou S, Autant-Bernard C (2019) Agglomeration externalities in Ecuador: Do urbanization and tertiarization matter? *Regional Studies* 53[5]: 706–719. CrossRef.

Han J, Ryu D, Sickles R (2016) How to measure spillover effects of public capital stock: a spatial autoregressive stochastic frontier model. In: Baltagi BH, Lesage JP, Pace RK (eds), *Spatial econometrics: Qualitative and limited dependent variables*. Emerald, 259–294. CrossRef.

Jia K, Qiao W, Chai Y, Feng T, Wang Y, Ge D (2020) Spatial distribution characteristics of rural settlements under diversified rural production functions: A case of Taizhou, China. *Habitat International* 102: 102201. CrossRef.

Kubara M, Kopczewska K (2024) Akaike information criterion in choosing the optimal k-nearest neighbours of the spatial weight matrix. *Spatial Economic Analysis* 19[1]: 73–91. CrossRef.

LeSage J, Pace RK (2009) *Introduction to spatial econometrics*. Chapman and Hall/CRC. CrossRef.

LeSage JP, Fischer MM (2008) Spatial growth regressions: model specification, estimation and interpretation. *Spatial Economic Analysis* 3[3]: 275–304. CrossRef.

López-Bazo E, Vayá E, Mora AJ, Suriñach J (1999) Regional economic dynamics and convergence in the European Union. *The Annals of Regional Science* 33[3]: 343–370. CrossRef.

Marrocu E, Paci R (2010) The effects of public capital on the productivity of the Italian regions. *Applied Economics* 42[8]: 989–1002. CrossRef.

Mera K (1973) Regional production functions and social overhead capital: An analysis of the Japanese case. *Regional and Urban Economics* 3[2]: 157–185. CrossRef.

Morales-Oñate V, Morales-Oñate B (2023) MTest: A bootstrap test for multicollinearity. *Revista Politécnica* 51[2]: 53–62. CrossRef.

Moreno Loza JL (2017) Incidencia del aumento sostenido del gasto público sobre el PIB en Ecuador: multiplicador fiscal para el período 2000–2015. B.S. thesis, PUCE

Munoz RM, Pontarollo N (2016) Cantonal convergence in Ecuador: A spatial econometric perspective. *Journal of Applied Economic Sciences* 11[1]: 39

Putra AS, Tong G, Pribadi DO (2020) Spatial analysis of socio-economic driving factors of food expenditure variation between provinces in Indonesia. *Sustainability* 12[4]: 1638. CrossRef.

Ram R (1996) Productivity of public and private investment in developing countries: A broad international perspective. *World Development* 24[8]: 1373–1378. CrossRef.

Szeles MR, Muñoz RM (2016) Analyzing the regional economic convergence in Ecuador. Insights from parametric and nonparametric models. *Romanian Journal of Economic Forecasting* 19[2]: 43–65