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

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13 November 2023

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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 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.

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.

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 the Gross Domestic Product (GDP). This investigation employs the VARS structural vector autoregressive model for 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's 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.

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:

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

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.

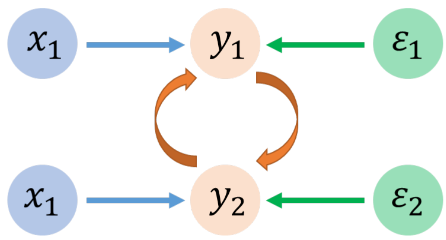

Figure 1: The Spatial Lag Model for Two Regions. Straight lines represent non spatial effects, curved lines are spatial effects

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's 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 Geographic Economics 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 a (robust) Lagrange Multiplier (LM), Likelihood Ratio (LR) and a Wald test.

Following this suggested strategy, a Spatial Lag Model was selected:

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

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:

Table 1: Data summary staticstics. Per capita values are shown in parenthesis.

Statistic	NOGVA	Private	Public	WAP	Population
Min	5,201,000 (858.40)	20,000 (0.88)	1	1,499	2,455
Q1	26,590,000 (1,764.70)	668,148 (313,029.00)	1,040 (0.08)	8,848	13,085
Median	58,690,000 (2,496.80)	1,632,026 (652,772.00)	10,680 (0.37)	18.760	28,080
Mean	421,500,000 (3,155.40)	5,504,143 (934,932.00)	6,305,760 (163,783.00)	54,127	77,199
Q3	193,800,000 (3,497.80)	4,679,626 (1,042,235.00)	304,575 (66,091.00)	39,856	60,519
Max	24,430,000,000 (32,627.60)	183,876,079 (10,794,984.00)	539,377,575 (6,713,234.00)	1,943,861	2,644,891

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

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

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

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. A distance matrix that compute the euclidean distances between the centroids of each spatial unit. The inverse distance matrix W consists of dividing 1 for the 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 116 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.

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 (*NOGVApp*), 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 6 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's 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's subtracted to preserve the asset owner's wealth. Consequently, the author contends that annual fluctuations in GDP or GVA aren't 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 employing a CC-based approach as a proxy for public capital, data from the National Public Procurement Service from 2017 is used.

The data entries in this source are recorded at the process level of contracting. However, they don't 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 wasn't 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 2)

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 7.

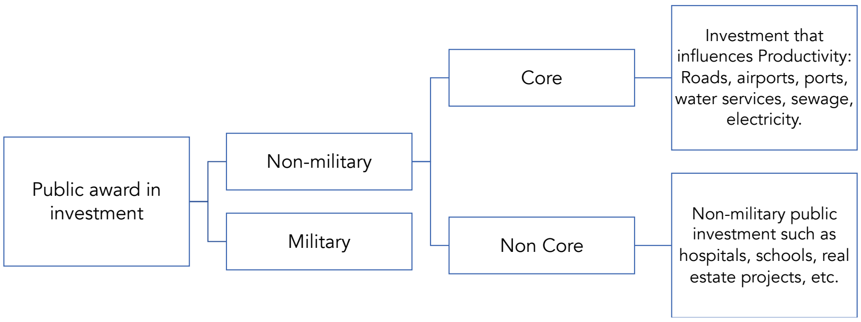

Figure 2: Public investment classification

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 8.

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 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. Canton concentration is shown in Figure 9.

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 a random spatial distribution of the observations. If the null hypothesis is rejected, it suggests that there's a discernible spatial pattern or structure embedded within the data.

Figure 3 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 3. 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 theese setups. In the 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 regression

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 4 presents both the LM test

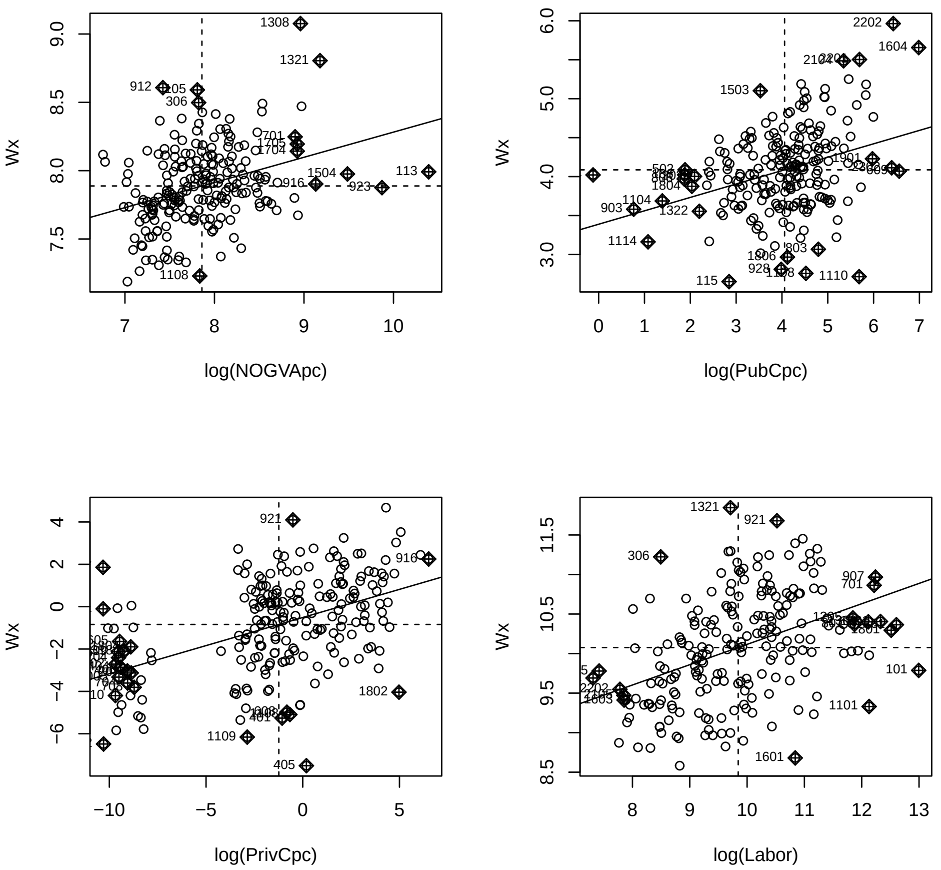

Figure 3: Moran plot for the logarithms of Non Oil Gross Value Added (NOGVApc), Public Capital per capita (PubCpc), Private Capital per capita (PrivCpc) and Labor

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. Non robust versions show significant p-values but robust counterparts do not.

Table 4 also presents different weights matrices. Contiguity weight matrix is a standard base approach, Distance (closest 5,10) let us examine the robustness of the estimation as more neighbours are included compared to the weight matrix without cut off. Inverse distance let us check the behaviour of model estimation *inverting* the weights as distance is greater. It is worth noting that, for regularity conditions, all weights are row-normalized. Traditional LM tests, considering all Contiguity and Distance (up to 10 closest) spatial weights matrices, 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.

Two last columns in Table 3 present p-values from LR and Wald tests. The null hypothesis in these cases the absence of spatial dependence, it is rejected in almost all cases. The first three columns in Table 3 show LR p-values of row-column model specifications: spatial autoregressive model (SAC), spatial durbin model (SDM), spatial lag model (SLM) and partial error model (SEM). For example, 0.7101 is the LR test p-value of comparing SDM and SLM. These 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 doesn't 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

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)			log(PrivCpc)			log(Labor)		
	Randomization	**Normal**	**Monte Carlo**	**Randomization**	**Normal**	**Monte Carlo**	**Randomization**	**Normal**	**Monte Carlo**	**Randomization**	**Normal**	**Monte Carlo**
MI[a]	0.2087	0.2087	0.2087	0.1662	0.1662	0.1662	0.2850	0.2850	0.2850	0.2622	0.2622	0.2622
E[MI][b]	-0.0047	-0.0047	-0.0042	-0.0047	-0.0047	-0.0041	-0.0047	-0.0047	-0.0041	-0.0047	-0.0047	-0.0049
V[MI][c]	0.0018	0.0018	0.0020	0.0018	0.0018	0.0020	0.0018	0.0018	0.0017	0.0018	0.0018	0.0018
z-value	4.9898	4.9645	4.7512	3.9911	3.9772	3.8430	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	0.0000	0.0000	0.0010	0.0000	0.0000	0.0010

[a]Moran's I Statistic.
[b]Expected Moran's I.
[c]Moran's I variance.

Table 3: 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

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

supports the use of Spatial Lag Model (SLM), it is the preferred method over Spatial Error Model (SEM).

5 Results

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 (1) Geographical contiguity, (2) k-nearest neighbors with $k = 5$, (3) k-nearest neighbors with $k = 10$, (4) Geographical distance without cut-off, and (5) Inverse distance.

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 isn't the case for other spatial weights specifications. When working with a geographically incomplete dataset, the concept of contiguity might not be suitable. While contiguity represents what could be seen as an absolute relationship, geographic distance concepts offer a perspective on relative relationships. Results show that contiguity specification is robust in relation to this point. It is worth noting that ρ decreases as distance grow. This is consistent with ρ being non significant in the inverse distance spatial weights specification.

The estimates of Model (3) are slightly higher than the coefficients in Models (1) and (2), coefficients of (0) are the highest. Estimated coefficients of public, private

Table 4: 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
Distance (closest 5)	12.357	0.000	0.036	0.850	14.788	0.000	2.467	0.116
Distance (closest 10)	4.346	0.037	0.235	0.628	6.887	0.009	2.776	0.096
Distance (no cut off)	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 5: Estimation Results in Spatial Lag Model.

	OLS		Contiguity		Distance (closest 5)		Distance (closest 10)		Distance (no cut off)		Inverse distance	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
(Intercept)	6.356	0.000	3.959	0.000	3.883	0.000	4.344	0.000	14.219	0.199	2.198	0.304
log(PubCpc)	0.099	0.002	0.094	0.002	0.093	0.002	0.098	0.002	0.098	0.002	0.097	0.002
log(PrivCpc)	0.036	0.000	0.031	0.001	0.036	0.000	0.035	0.000	0.036	0.000	0.036	0.000
log(Labor)	0.117	0.000	0.109	0.000	0.106	0.001	0.112	0.000	0.116	0.000	0.113	0.000
ρ			0.315	0.000	0.330	0.001	0.262	0.047	-0.998	0.246	0.211	0.211
Log-likelihood	-146.7143		-140.3441		-140.703		-144.7379		-146.0412		-145.9331	

Table 6: Direct and Indirect Output Elasticity Estimates.

	Contiguity		Distance (closest 5)		Distance (closest 10)		Distance (no cut off)		Inverse distance	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
log(PrivCpc)										
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(PubCpc)										
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

and labor variables are significant at 5% in almost all cases. Ecuador's public capital contributes 9.4% of the production. Other components, like private investment and labor, contribute 3.1% and 10.9% in model (1), respectively. The impact of spatial lags on the dependent variables is notably large at 31.5%. 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.

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 1.36% wit 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 5 neighbours. However, significance of indirect impacts is lost in the rest of spatial weights matrix specifications.

Taking into account the total effect of public capital on economic performance, 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 $0.0317 - 0.0136 = 0.018$, 1.8%. For labor and private capital, the feedback effect is 6.3% and 5.5% in Model (1) 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.

Leveraging the spatial contiguity weights matrix, 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) and identify which units are more reliant on their neighboring regions

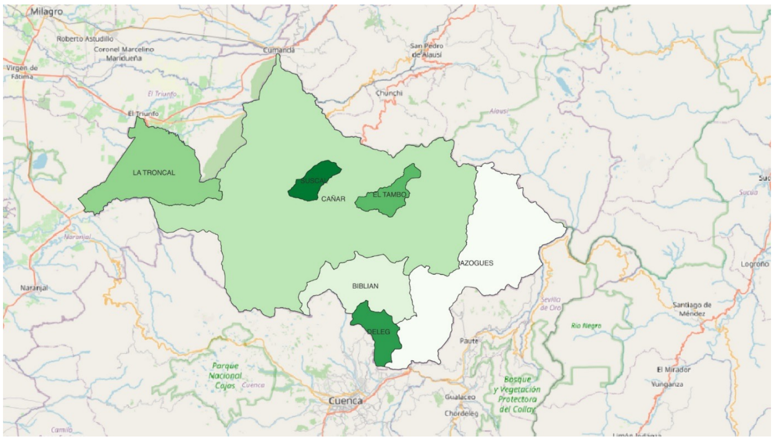

Figure 4: Cañar

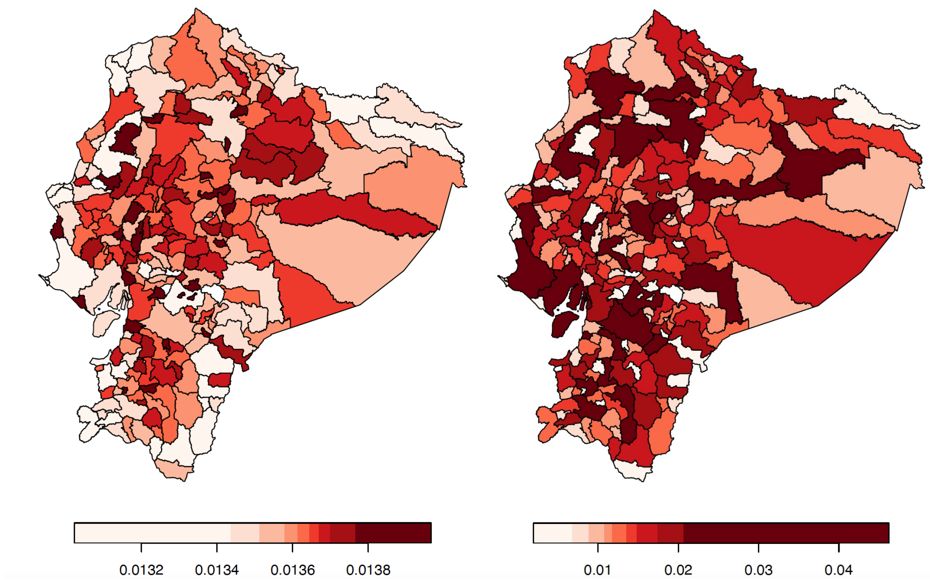

Figure 5: Row (left) and Column (right) effects

(row effects). Figure 5 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. Nonetheless, it is crucial to note that this canton has two unique interior neighbors, which exclusively share a border with Cañar (see Figure 4). 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 Gross Value Added (GVA), which are not decisive factors in determining the observed impact of public investment. Spatial structures play a significant role in this regard.

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 3.4%.

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.

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

Row effects in Table 8 can be interpreted as follows. In the case of the Rumiñahui

Table 7: Column effects.

					GVA		Population	
Rank Col.Eff.	Code	Canton	Province	Column effect	Rank	Value	Rank	Value
1	303	CAÑAR	CAÑAR	0.0462	55	192,390,383	49	66,996
2	1109	PALTAS	LOJA	0.0348	144	36,163,641	122	24,017
3	2401	SANTA ELENA	SANTA ELENA	0.0342	27	417,373,082	17	176,373
4	1701	D.M. QUITO	PICHINCHA	0.0337	1	24,426,597,900	2	2,644,145
5	1303	CHONE	MANABI	0.0322	35	314,327,442	21	131,877
6	101	CUENCA	AZUAY	0.0315	3	4,392,835,893	3	603,269
7	901	GUAYAQUIL	GUAYAS	0.0305	2	20,554,798,446	1	2,644,891
8	1201	BABAHOYO	LOS RIOS	0.0289	16	905,261,666	18	171,038
9	1501	TENA	NAPO	0.0277	42	255,159,287	45	74,158
10	804	QUININDE	ESMERALDAS	0.0261	20	655,491,210	20	140,670

Table 8: Row effects.

					GVA		Population	
Rank Row.Eff.	Code	Canton	Province	Row effect	Rank	Value	Rank	Value
1	305	EL TAMBO	CAÑAR	0.0140	113	56,500,676	168	11,673
2	307	SUSCAL	CAÑAR	0.0140	186	15,269,624	200	6,128
3	921	PLAYAS	GUAYAS	0.0139	78	108,585,168	61	54,308
4	1305	FLAVIO ALFARO	MANABI	0.0139	130	44,499,752	116	24,615
5	605	CHUNCHI	CHIMBORAZO	0.0139	153	30,696,591	164	12,982
6	1705	RUMIÑAHUI	PICHINCHA	0.0138	18	803,979,272	25	107,043
7	903	BALAO	GUAYAS	0.0138	107	59,324,110	115	24,777
8	1319	PUERTO LOPEZ	MANABI	0.0138	141	41,454,460	126	23,689
9	2302	LA CONCORDIA	S.T. DE LOS TSACHILAS	0.0138	73	121,913,902	68	50,241
10	907	DURAN	GUAYAS	0.0138	9	1,484,310,229	7	293,005

canton, on average, an increase of one percentage point in public capital in its surrounding cantons increases its economic performance by 1.38%.

6 Conclusions

The findings indicate that in Ecuador, production factors, especially public capital, establish spatial relationships among the cantons. This is 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, while the non-spatial or direct effect (0.032) corresponds to 70%. 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's 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.

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.

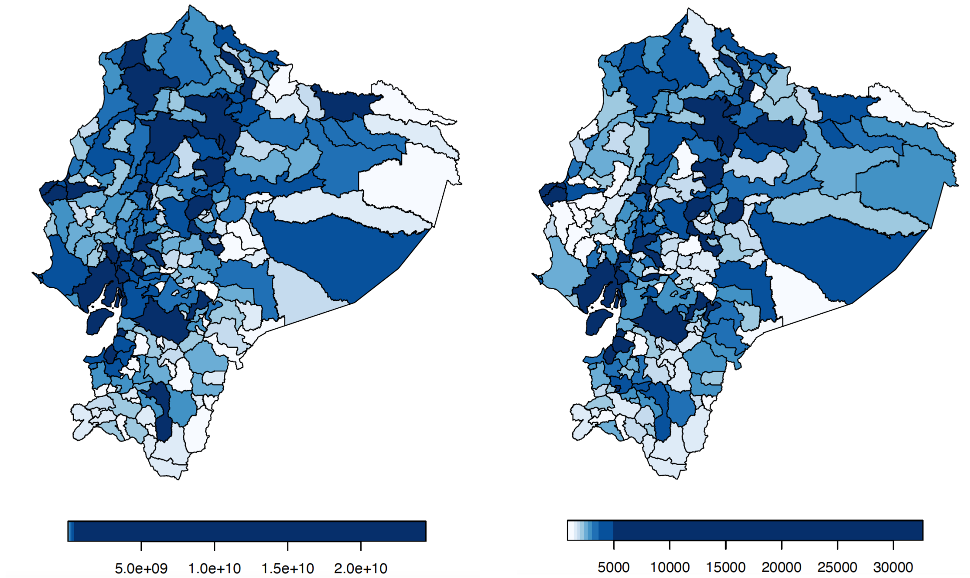

Figure 6: Non-oil Gross Value Added (left panel) and per capita values (right panel)

A Choropleth maps

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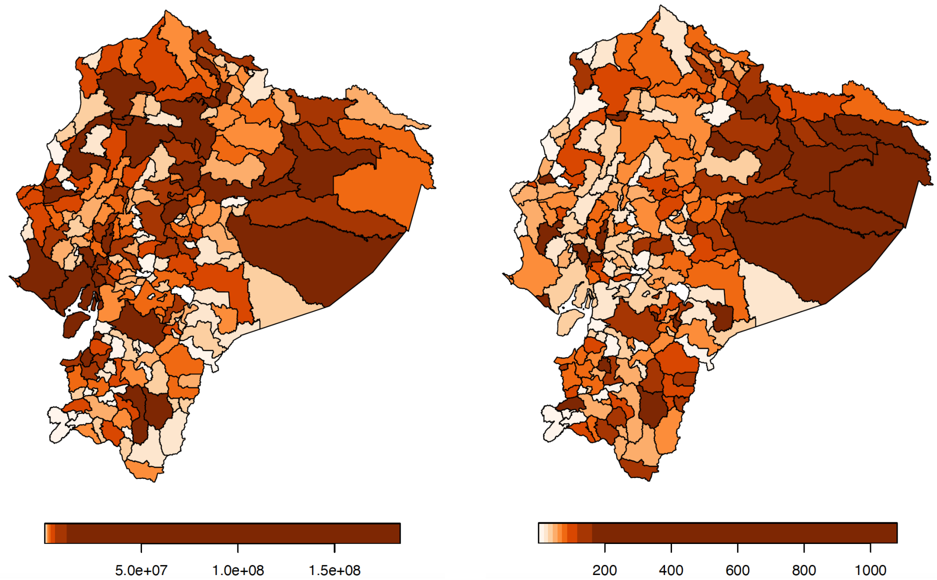

Figure 7: Public investment (left panel) and per capita values (right panel)

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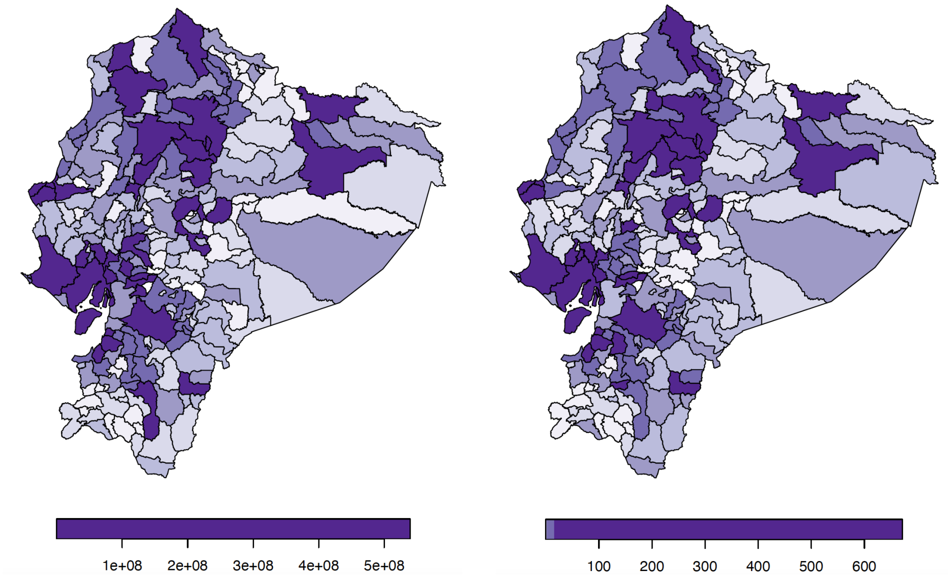

Figure 8: Private investment (left panel) and per capita values (right panel)

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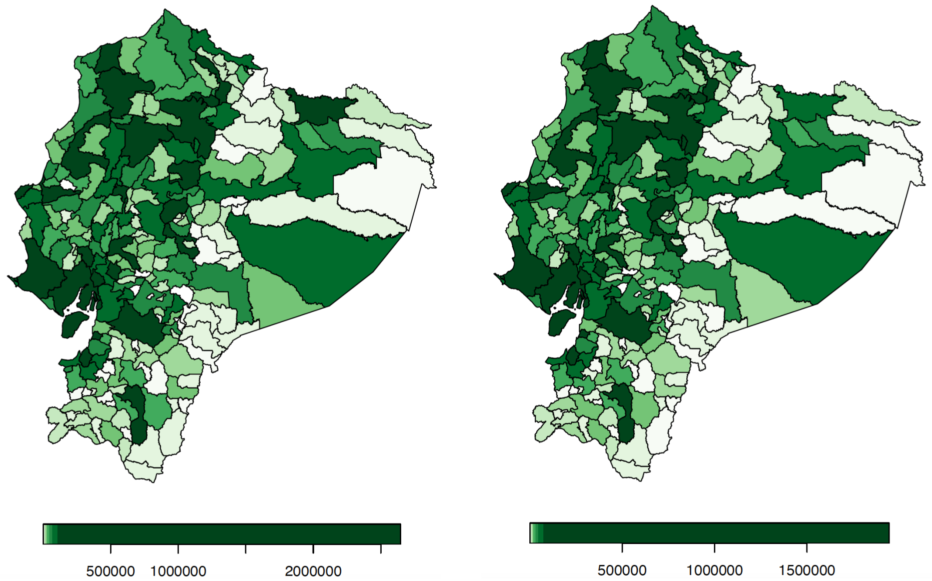

Figure 9: Population (left panel) and Working age population (right panel)