Manufacturing remunerations and labor productivity, as well as other determinants, at the municipal level in Mexico, from 2003 to 2018

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Abstract

The aim of this research is to identify and analyze the main determinants, in addition to labor productivity, of wages in Mexico's manufacturing sector from 2003 to 2018. The information from the economic censuses of INEGI is used for this purpose. Additionally, the information has been supplemented with data from the National Commission for the Search of the Ministry of the Interior and data from the demography and society section of INEGI. This study considers the territorial dimension and the impact that the economic characteristics of neighboring municipalities have on local wages due to their geographical proximity. To achieve this objective, spatial econometrics specifications have been used that consider the influence that neighboring municipalities have on local wages. A model is presented where around 5 explanatory variables and 11 control variables at the municipal level are included. The results indicate that there is a positive spatial relationship between wages and labor productivity at the municipal level of 0.28 pp to 0.3 pp., depending on the model and the measure of labor productivity.

1. Introduction

Since the entry into force of the North American Free Trade Agreement (NAFTA), it has been expected that, according to economic theory, Mexico would observe an increase in its real wages. The theory postulates that if there are no barriers to the trade of goods and services, there should be a tendency towards the equalization of the prices of the factors of production: labor and capital (Stolper and Samuelson, 1941). Subsequently, Mundell (1957) demonstrated that there was an equalization effect in factor prices through free trade or direct mobility of productive factors indistinctly.

In this case, it was expected that Mexico, being a country abundant in labor, would specialize in goods intensive in this factor, resulting in a competitive economy in the world market and in constant growth (Ruiz Nápoles, 2020). Over time, the Mexican economy would tend to distribute the income from this economic growth among the productive factors (Hernández Mota, 2018). Behind this, there are microeconomic considerations: it is expected that, with economic growth, the marginal productivity of labor would be higher than the real wage, so companies would find it profitable to hire more labor and would push wages up (Argoti Chamorro, 2011; Vera and Vera, 2021). However, it is widely recognized that wage and labor productivity differences persist between regions, states, and municipalities in Mexico.

The importance of economic compensation, or wages, lies in being among the main factors influencing an individual's well-being. Wages have the function of covering individuals' needs, taking into account the cost of living such as housing, food, and clothing. At the same time, wages are related to the value added they generate and labor productivity. Now, given the Mexican economic context, is there a relationship between wages and labor productivity? What are the factors that influence compensation or wages? Furthermore, is territory a factor influencing the relationship between wages and labor productivity? Previous studies have shown that, at the state level, there is a positive relationship between wages and labor productivity, as well as that the latter has an effect on the wages of neighboring states (González Mata, López Cabrera & Cabral Torres, 2022).

In view of the above, this study aims to identify and analyze the determinants of wages in Mexico's manufacturing sector from 2003 to 2018. For this purpose, the analysis is disaggregated at the municipal level, and spatial econometric techniques are used. The manufacturing sector is studied because it is the main sector favored during the Mexican economic liberalization process, as well as in the formation and subsequent development of the North American Free Trade Agreement (NAFTA) in 1994, and the United States-Mexico-Canada Agreement (USMCA) in 2018. The outsourcing processes of North American companies led Mexican companies to integrate into global value chains, which favored the manufacturing sector in general and the automotive sector in particular (Medina Chamorro & De la Peña Cardenas, 2015).

For better readability, this document is divided as follows: the next section provides a brief literature review on the main determinants of wages in the context of economic theory, as well as some empirical studies. The third section of this work involves the detail of the methodology and data used in this article. Finally, the essay concludes with an exposition and analysis of both the results obtained and the conclusions, acknowledging the main contributions and limitations.

2. Brief review of relevant literature

Traditional economic theory postulates that, in the long run, the increase in labor productivity will have a positive impact on the increase in real wages (Mankiw, 2015). Regional economic theory postulates that, at that level, there is also a transfer of aggregate labor productivity to workers through better wages (Turok, 2004). Some theoretical currents - such as human capital theory - mention that more productive workers tend to receive higher rewards (Maringe, 2015).

Therefore, it is believed that labor productivity is linked to education and skills (Schultz, 1960, 1961; Becker, 1964), that is, education is a key factor that facilitates technological diffusion and, as a result, boosts labor productivity (Nelson & Phelps, 1966). Additionally, education enables the transfer of knowledge among workers and between generations, which translates into greater growth and better conditions for all (Kremer & Thomson, 1988). But not only education, labor productivity and wages are also linked to workers' experience (Mincer, 1974). As a corollary, in this theoretical current, it is understood that companies pay higher wages to those employees who possess the skills and knowledge that are most valuable to them (Cardona et al., 2007).

In that sense, supply and demand in the labor market also play an important role in the relationship between labor productivity and wages. If there is high demand for certain skills in the labor market and a limited supply of workers with those skills, wages tend to increase. On the other hand, if there is an oversupply of workers for certain jobs, wages can remain low. That is, both the size of the labor market and the population as well as qualifications have an effect on both variables. In the case of Latin America and the Caribbean, there is a deficit of qualified workers for certain jobs while, for others with lower requirements, there is an oversupply (Gontero & Novella, 2021). In a joint report by the OECD, ECLAC, and CAF (2017), it is mentioned that companies in the region face higher odds of severe operational problems due to the shortage of human capital here than in Southeast Asia. This is influenced by both deficiencies and inequalities in the educational system, as well as the limited availability and relevance of training programs, which partly explain the skill shortages reported by employers (Huepe, Palma & Trucco, 2022). This despite the improvement in access to education experienced in recent years.

Additionally, there are other wage determinants that, together with labor productivity, affect it at an aggregate level. For example, Blanchflower and Oswald (1994) considered variables such as age, sex, education, race, unionization, and sector of economic activity in their study, finding a significant relationship. In this sense, workers can negotiate collectively through unions to improve their working conditions and wages. Therefore, the capacity for collective bargaining can influence the relationship between labor productivity and wages.

The relationship between labor productivity and wages can also be influenced by macroeconomic factors, such as inflation, the cost of living, and unemployment. Wages can increase in response to increases in the prices of goods and services and decrease with rising unemployment. Phillips (1958) found that there was an inverse relationship between the level of unemployment, inflation, and economic compensation to workers. This could be exacerbated or mitigated according to the implementation of certain economic policies. Government policies, such as the minimum wage and other labor regulations, can also influence the relationship between labor productivity and wages (Moreno-Brid, Garry & Monroy-Gómez-Franco, 2014)[1]. These policies can influence workers' ability to earn wages that reflect their productivity.

Government policies and regulations are part of the country's institutional framework. In that sense, labor productivity and wages are also influenced by institutional factors (Kaldaru & Parts, 2008). And in developing countries, such as Mexico, institutional and contextual factors are more relevant in explaining labor productivity (Gamero Requena, 2012). For example, political stability reduces uncertainty, allowing companies to plan for the future. A stable political environment is likely a key factor in determining whether companies are prepared or not to undertake new investment projects - especially foreign companies - as it reduces risk (Jensen, 2003; Hvozdyk & Mercer-Blackman, 2010). Additionally, some authors (Besley et al., 2010; Acemoglu et al., 2014) postulate that there is a positive relationship between greater political competition and positive economic outcomes.

In that case, an environment with low crime rates also affects labor productivity and wages. For example, homicides and robberies have a statistically significant negative effect on FDI, which in turn would have a negative effect on the labor productivity-wage relationship (Cabral, Mollick & Saucedo, 2018). The sectoral characteristics of companies also show a significant relationship with wages and labor productivity. For example, there is evidence that there is a positive relationship between labor productivity and wages with the manufacturing exports of Mexican companies (Jaime Camacho, 2011), as well as with foreign direct investment (FDI) (Alamilla-Gachuz, Cervantes-Siurob, & Lengyel, 2020; Rangel González & López

[1] In Mexico, there are a several studies recently published about the effects of a minimum wage increment on Mexican labor markets (Campos Vázquez, Esquivel and Santillán Hernández, 2012; Campos-Vazquez and Esquivel, 2021); on prices (Calderón Cerbón et al., 2022); and on poverty (Campos-Vazquez and Esquivel, 2023).

Ornelas, 2022). This could be a consequence of the incorporation of technological innovation in the products and services that exporting companies, many of them with FDI, supply. The introduction of new technologies changes the nature of work and affects the relationship between labor productivity and wages. Recent advances in artificial intelligence and machine learning, for example, increase productivity and, at the same time, impact the labor market by requiring certain labor skills (Saunders, 2019).

Territory can also influence the relationship between labor productivity and wages. Spatial economic disparities can be influenced by geographic factors (Krugman, 1991; Fujita, Krugman and Venables 1999). Agglomeration economies can decrease costs on some key factors that can influence remunerations versus labor productivity relationship. Like those are technological innovation, educational level, infrastructure and access to markets, sectoral composition, and institutions at the regional level. For example, Camberos, Huesca Reynoso and Castro Lugo (2013) showed that in Mexico regions that had greater technological development experienced higher labor productivity and higher wages. This relationship is often observed in regions with sectors based on cutting-edge technologies (such as the automotive, petrochemical, or pharmaceutical industry) or knowledge-based industries (for example, ICTs). That is why there is a positive relationship between regions with a highly educated and skilled workforce with higher labor productivity and higher wages (Galassi & Andrada, 2011; López Cabrera, 2022). Therefore, investments in education and training can have a positive impact on both productivity and wages.

Likewise, regions with better infrastructure, such as airports, roads, ports, etc., have better access to national and international markets and experience higher labor productivity and higher wages. This is influenced by lower transportation costs and better market opportunities (Rozas & Sanchez, 2004). The sectoral composition in a region can also affect the relationship between labor productivity and wages. For example, regions with a high concentration of high-tech industries may have higher labor productivity and wages compared to regions with a more traditional industrial base (Ciaschi, Galeano & Gasparini, 2021). Factors such as local labor market regulations or even differentiators such as different levels of the minimum wage, levels of unionization, and wage bargaining mechanisms can also influence the relationship between labor productivity and wages regionally (López Machuca & Mendoza Cota, 2017).

This study considers some variables mentioned in previous studies, given the availability of information at such a disaggregated level as the municipal level and for such a large developing country as Mexico. However, it is recognized that the relationship between labor productivity and wages is a complex issue that can vary by sector, region, labor and economic policies, among others. It is important to note that the relationship between labor productivity and wages also varies depending on the economic situation and the specific conditions of each country. Additionally, equity and income distribution are also important considerations in the discussion on this topic.

3. Methodology

To achieve the objective of this research, we need to define the source of information for our data and the scope of it. Also, the general procedure of our analysis. As mentioned before, the objective is to analyze the spatial relationship between wages and labor productivity across municipalities in Mexico from 2003 to 2018. To do this, control variables are defined that could affect the distribution of wages and labor productivity. Subsequently, different spatial weight matrices are created to define the neighbors that each municipality will have. The use of spatial econometric models is justified by identifying the spatial dependence of wages in municipalities, using the global Moran's index (Moran, 1948). Then we perform a spatial descriptive analysis by creating clusters of local spatial dependence using the local Moran's index (Anselin, 1995). After justifying the use of spatial econometric models, we calculate the spatial relationship between wages and labor productivity using a dynamic spatial panel model. Finally, we perform statistical robustness tests to strengthen the results.

3.1. Variables and their sources

Based on González Mata, López Cabrera, and Cabral Torres (2022) and Elhorst (2021), a set of variables are used to estimate the empirical model. This allowed us to test the spatial relationship between wages and labor productivity among Mexican municipalities. The variables can be divided into 1) dependent variable, 2) explanatory variables, and 3) control variables. The variables are shown in table 1.

Table 1. Variables and Acronyms

Variable	Acronym	Classification	Calculation Formula	Source
Remuneration per worker in the manufacturing sector	Remunerations	Dependent	Total remuneration of the manufacturing sector in municipality i year t / Total workers of the manufacturing sector in municipality i year t	INEGI
Manufacturing sector productivity based on hours worked	Productivity b. hours worked	Explanatory	Manufacturing production in municipality i year t / Hours worked in the manufacturing sector of municipality i year t	INEGI
Manufacturing sector productivity based on number of workers	Productivity b. workers	Explanatory	Manufacturing production in municipality i year t / Total workers in the manufacturing sector of municipality i year t	INEGI
Employment rate	Occupation	Explanatory	Employed population in municipality i year t / Total population in municipality i year t	INEGI

Manufacturing exports per worker	Exports	Explanatory	Total manufacturing exports in municipality i year t / Manufacturing sector production in municipality i year t	INEGI
Foreign direct investment per worker in the manufacturing sector	Foreign direct investment	Explanatory	Foreign direct investment in municipality i year t / Manufacturing sector production in municipality i year t. Foreign direct investment is considered as the participation of foreign capital in manufacturing sector enterprises.	INEGI
Population density	Population density	Explanatory	Population in municipality i year t /	INEGI
Control Variables	**Acronym**	**Classification**	**Calculation Formula**	**Source**
Political concentration	Political concentration	Control	Sum of total votes per political party squared in the nearest election in municipality i year t / Sum of total votes in the nearest election in municipality i year t	INE
Population proportion by age group	Population by age group	Control	Population by age group in municipality i year t / Total population in municipality i year t	INEGI
Control Variables (based on ILOSTAT classification)	**Acronym**	**Classification**	**Calculation Formula**	**Source**
Population proportion by age group	Population by age group (ILOSTAT)	Control	Population by age group in municipality i year t / Total population in municipality i year t	INEGI
Regional Dichotomous Variables	**Acronym**	**Classification**	**Calculation Formula**	**Source**
Regional dichotomous variable (Central)		Control	State-level dichotomous variable: 1 if the state is within the specified region, 0 otherwise	INEGI

Regional dichotomous variable (Western)		Control		
Regional dichotomous variable (Northern)		Control		
Regional dichotomous variable (Southeast)		Control		
Additional Control Variables	**Acronym**	**Classification**	**Calculation Formula**	**Source**
Disappeared persons per 100 thousand inhabitants	Disappeared persons	Control	Disappeared persons in municipality i year t / Population in municipality i year t * 100,000	Secretariat of Governance

Source: Prepared by authors.

3.2. Construction of the spatial weights' matrix

The construction of the spatial weights' matrix is the most important step in building empirical spatial econometric models. The way the spatial weights matrix is constructed defines which municipalities are neighbors or have spatial contiguity. There are many ways to construct a weights matrix or spatial weighting, but the two most common approaches are contiguity and distance criteria (Anselin, Syabri, & Kho, 2009). We understand contiguity when two spatial units share a common border or boundary. There are two types of contiguity:

Rook contiguity is when two spatial units share a common border or boundary, so they are considered neighbors (see figure 1.1). While queen contiguity is when two spatial units only share a common border between them, thus they are considered neighbors (see figure 1.2).

Figure 1.1. Neighbors (yellow squares) of a spatial unit (red square) in matrix with queen contiguity

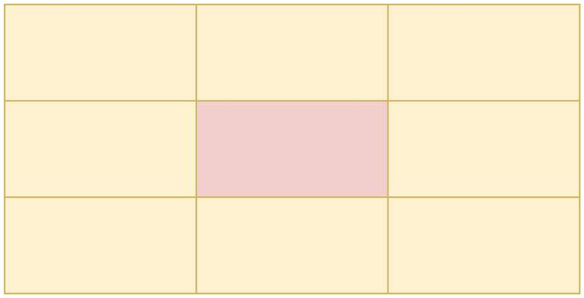
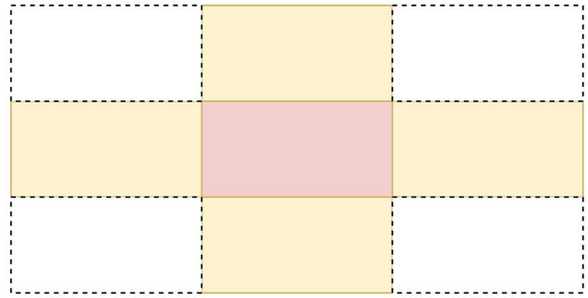


Figure 1.2. Neighbors (yellow squares) of a spatial unit (red square) in a matrix with rook contiguity



Once we define the type of contiguity, we can calculate distance. There are two types of distance:

- Distance band: All municipalities within a buffer or distance band from the municipality are considered neighbors.
- k-nearest neighbors: The k nearest municipalities to a municipality are considered neighbors.

For this document, we use the queen contiguity matrix and the distance of the k-nearest neighbor, with k = 1, 2, 3, 4, 7, using a shapefile from INEGI and the Geoda software[2].

3.3 Spatial Dependence

To identify spatial dependence, we calculate the Moran's I statistic (Moran, 1948), which measures the global spatial autocorrelation[3] of the average of the explanatory variables over the study period (Kitchin & Thrift, 2009). The statistic is defined as:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \ldots (1)$$

where w_{ij} is the ij of the spatial weights matrix W for municipality i and neighboring municipalities j,while N is the number of observations, with $i \neq j$ and $w_{ij} = 0$. Where z_i y z_j represent the deviation from the mean of an attribute for i $(x_i - \underline{X})$ o j $(x_j - \underline{X})$, here $x$is the remuneration per worker.

[2] Available at https://geodacenter.github.io/
[3] Spatial autocorrelation exists when a variable exhibits a regular pattern in space, where its values at a set of locations depend on the values of the same variable at other locations (Odland, 2020).

The W matrix can be represented as:

$$\begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{pmatrix}$$

where each spatial unit is represented by a row i, and potential neighbors by columns j. w_{ij} represents each spatial weight, such that $w_{ij} > 0$when i and j are neighbours, and $w_{ij} = 0$ otherwise. The spatial matrices constructed for this article have a "row-standardized form," meaning $w_{ij(s)} = w_{ij}/\sum_j w_{ij}$ which ensures $\sum_i \sum_j w_{ij(s)} = n$. Then, equation 1 can be simplified as:

$$I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij(s)} z_i z_j}{\sum_{i=1}^{n} z_i^2} \ldots(2)$$

The inference of this statistic is based on the null hypothesis of spatial randomness, while the alternative hypothesis is the existence of clustering. In identifying the clustering hypothesis, the location and selection of clusters can be identified using the local Moran statistic - following Anselin (1995) - with the following equation:

$$I = \frac{z_i \sum_{j=1}^{n} w_{ij(s)} z_j}{\sum_{i=1}^{n} z_i^2} \ldots (3)$$

For the identification of local spatial clusters and outliers, conditional randomization or permutation will be used, following Anselin (1995). Conditional randomization is used to produce levels of pseudo-significance. Randomization is conditional because the value z_i at location i is held fixed (not permuted), and the remaining values are randomly permuted among the locations in the dataset (one for each location). Statistically significant locations can be classified as High-High and Low-Low spatial clusters and High-Low and Low-High spatial outliers (Anselin, Syabri, & Kho, 2009), which will be presented in this study for the different outcome variables.

3.4. Econometric Spatial Models and the Empirical Model

In this section, we explain the theoretical background of spatial econometric models and then describe the empirical model proposed in this document.

3.4.1. Spatial Econometric Models

The most common approach in spatial econometrics for cross-sectional data is to start with the Ordinary Least Squares (OLS) model and then test whether the model needs to be expanded with spatial effects (Elhorst 2014), considering different interaction effects. The OLS model is:

$$Y = \alpha + X\beta + \varepsilon \ldots (4)$$

donde Y is a vector Nx1 of the independent variable for each unit of the sample $i = 1, \ldots, N$, X indicates the NxK matrix of covariates, and β is the Kx1 vector of parameters. ε is the error term that is assumed to be independent and identically distributed with zero mean and constant variance. σ^2.

There are three types of interaction effects to test spatial dependence:

- Endogenous interaction effects: the dependent variable of unit i (y_i) interacting with with the dependent variable of unit j (y_j), and viceversa.
- Exogenous interaction effects: the dependent variable of a particular unit i (y_i) interacting with the independent variable of another unit j (X_j).

Interaction effectts of error terms: The error term of unit i interacts with the error term of unit j, and vice versa. With these interactions, Elhorst (2014) constructs the General Nesting Spatial (GNS) model.

$$Y = \alpha + \delta WY + X\beta + WX\theta + u \ldots (5)$$

whew u :

$$u = \lambda Wu + \varepsilon \ldots (5a)$$

Where WY represents endogenous interaction effects, WX represents exogenous interaction effects, and Wu represents interaction effects in terms of errors. The term ρ is the autoregressive coefficient, λ is the coefficient of spatial autocorrelation, and β are the unknown parameters. The combination of these interactions generates the different types of spatial econometric models shown in Table 2. These models are classified according to Elhorst (2021) as the first generation of spatial econometric models.

Table 2. Spatial Econometric Models

Model	Spatial Lags
Ordinary Least Squares, OLS (MCO model)	-----
Spatial Autoregressive Model, SAR (lag model)	WY
Spatial Error Model, SEM	Wu
Spatial Lag of X Model	WX
Spatial Autoregressive Combined Model, SAC (SARAR model)	WY, Wu
Spatial Durbin Model, SDM	WY, WX
Spatial Durbin Error Model, SDEM	WX, Wu
General Nesting Spatial Model, GNS	WY, WX, Wu

Source: Prepared by authors based on Elhorst (2014).

The second generation of spatial econometric models consists of non-dynamic or static spatial panel data models, while the third generation encompasses dynamic spatial panel data models. In the third generation, the SDM model shown in Table 2 can be extended as follows:

$$Y_t = \alpha + \tau Y_{t-1} + \delta W Y_t + \nu W Y_{t-1} + X_t \beta + W X_t \theta + \lambda_t \iota_N + e_t \ldots(6)$$

with time t where $t = 1, \ldots, T$.

Finally, the fourth generation of models adds the common factor approach to those of the third generation. The fourth-generation models culminate with the Dynamic General Nested Spatial Econometric Model for Spatial Panels with Common Factors (DGNSCF). It is the most advanced model structure currently available.

This model is useful for measuring:

- Local spatial dependence through endogenous spatial lags, exogenous spatial lags, and a spatial lag in the error term.
- Dynamic effects using lagged dependent variables in time and space.
- Global cross-sectional dependence using cross-sectional averages or principal components with heterogeneous coefficients, which generalizes traditional controls for variables invariant over time and space using unit-specific and time-specific effects.

In our case, we consider that DGNSCF is useful because there is a relationship between remuneration over time and with neighboring municipalities, as well as with productivity.

The DGNSCF model can be defined as:

$$Y_{i,t} = \alpha + \tau Y_{i,t-1} + \delta W Y_{i,t} + \nu W Y_{i,t-1} + X_{i,t}\beta + W X_{i,t}\theta + e_{i,t} + \Gamma_r^T f_{r,t} \tag{7}$$

where $e_{i,t} = \lambda W e_{j,t} + \varepsilon_t$ and $\sum_r \Gamma_r^T$ represent the parameters and $f_{r,t}$ represents the common factor r where $r = 1, \ldots, R$. Then, the number of common factors are $N + T$.

Instead of spatial and temporal fixed effects, a model with common factors can be measured in two ways: 1. by taking the temporal and cross-sectional averages of the observable variables, or 2. through principal components.

3.4.2. The empirical model

To define the empirical model, we employ an SDM model with common factors following the model proposed by González Mata, López Cabrera, and Cabral Torres (2022), based on Elhorst (2021). The empirical model follows the equation:

$$ln\, rem_{i,t} = \theta ln\, rem_{i,t-1} + \delta W ln\, rem_{j,t} + \eta W ln\, rem_{j,t-1} + \beta ln\, X_{i,t} + \gamma W ln\, X_{j,t} + \varepsilon_{i,t} + \Gamma_r^T f_{r,t} \quad (8)$$

Where $rem_{i,t}$ represents the remuneration per worker in municipality i time t; W is the spatial matrix; and $X_{i,t}$ is the covariates vector in municipality i time t; and $\varepsilon_{i,t}$ is the error term. $\sum_r \Gamma_r^T$ represents the parameters and $f_{r,t}$ the common factor r where $r = 1, \ldots, R$.

As mentioned earlier, instead of spatial and temporal fixed effects, a model with common factors can be measured in two ways: by taking the temporal and cross-sectional averages of the observable variables or through principal components. For the purpose of this research, we propose to construct the model using the temporal and cross-sectional averages of the variables based on Elhorst (2021). The justification for using an SDM with common factors for this research is that, as discussed in section 4 (Data and Descriptive Statistics), there is heterogeneity in the variables involved. Additionally, we calculate the Cross-Sectional Dependence (CD) test proposed by Pesaran (2015), where the null hypothesis is that there is cross-sectional independence, and the alternative hypothesis is that there is cross-sectional dependence.

Furthermore, we calculate an SDM model with random time and space effects and compare it with the results of the SDM model with common factors.

4. Data and Descriptive Statistics

The table below presents the descriptive statistics of the variables considered in the empirical model. It is noteworthy that both the dependent variable and the independent variables, with the exception of the employment rate, exhibit high levels of standard deviation. This indicates heterogeneity among municipalities in these variables. This heterogeneity is crucial for our analysis because, when using a spatial model that considers fixed time and space (municipalities) effects, a homogeneous impact of municipalities in each year is assumed. On the other hand, by employing a methodology that considers common factors, we can identify how municipalities may respond in a lesser or greater manner compared to others.

Table 3. Descriptive Statistics

Variable	N	Mean	Std. dev.	Min.	Max.
Productivity based on hours worked	9,580	0.287	1.064	0.000	37.539

Productivity based on number of workers	9,580	0.666	2.494	0.000	84.320
Remunerations	9,580	47,626.538	79,577.679	1.343	1,071,889.717
Exports	8,004	0.012	0.075	0.000	0.989
Foreign Direct Investment	9,832	0.003	0.020	0.000	1.000
Employment Rate	9,580	0.318	0.061	0.044	0.581
Population Density	9,578	3.940	1.654	-2.083	9.876
Missing Persons	9,580	3.276	20.406	0.000	1,065.112
Population under 20 years	9,580	0.428	0.068	0.000	0.630
Population between 20 and 29 years	9,580	0.151	0.026	0.000	0.262
Population between 30 and 39 years	9,580	0.128	0.022	0.000	0.429
Population between 40 and 49 years	9,580	0.101	0.020	0.000	0.375
Population between 50 and 59 years	9,580	0.076	0.019	0.000	0.263
Population over 60 years	9,580	0.113	0.050	0.000	0.667
Political Concentration	9,470	0.302	0.092	0.065	1.000
Regional Dummy (Center)	9,832	0.483	0.500	0.000	1.000
Regional Dummy (West)	9,832	0.187	0.390	0.000	1.000
Regional Dummy (North)	9,832	0.138	0.344	0.000	1.000
Regional Dummy (Southeast)	9,832	0.193	0.395	0.000	1.000

Source: Prepared by authors.

In the literature review section, we analyzed how, based on economic theory, the relationship between productivity and remuneration can be explained through a spatial model. The technical justification is provided through the global Moran's index. The global Moran's index calculates the spatial autocorrelation of a variable. By identifying spatial autocorrelation, the use of spatial econometrics models to calculate the relationship between remuneration and productivity can be technically justified. As shown in Table 4, there is a positive and significant autocorrelation of the remuneration variable in all considered spatial matrices. This justifies the use of spatial econometrics models. Additionally, we chose the queen matrix to run our empirical models as it presents the highest spatial correlation (0.11).

Table 4. Global Moran's I Statistics by W Matrix of Remuneration Variable

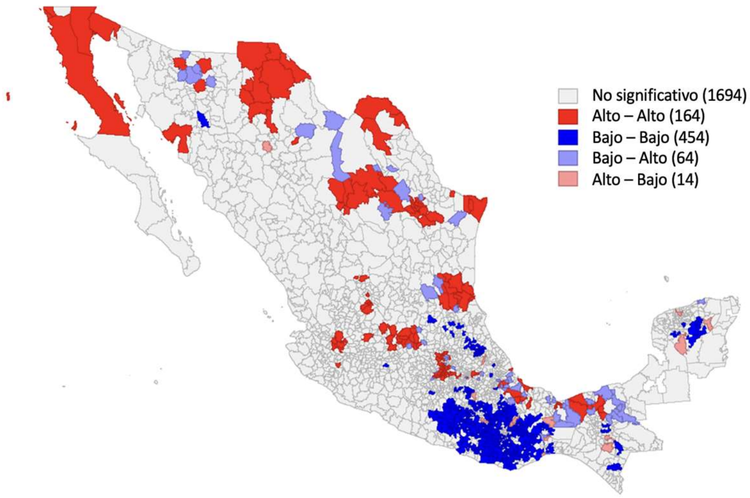
W Matrix	Standard Deviation	Global Moran's I	Variance
Queen	5.55	0.11***	0.00037
K=1	2.07	0.06***	0.00096
K=2	3.48	0.08***	0.00057
K=3	4.23	0.08***	0.0004
K=4	4.96	0.09***	0.00031
K=7	5.63	0.07***	0.00018

Source: Prepared by authors.

Note: * p<0.05, ** p<0.01, *** p<0.001

For additional analysis, we computed the local Moran's I index for the dependent variable and the explanatory variables. Figure 2 presents the local Moran's I index for the remuneration variable. As observed, clusters of municipalities with high levels of remuneration (red color) are located in the northern and central regions of Mexico, as well as some near the Gulf of Mexico (which can be explained by oil production in these municipalities). On the other hand, clusters of municipalities with low levels of remuneration are found in the southern and eastern (Yucatán Peninsula) regions of the country (navy blue color). Additionally, it is the variable that exhibits the highest number of clusters with a low-low relationship, with 454 municipalities.

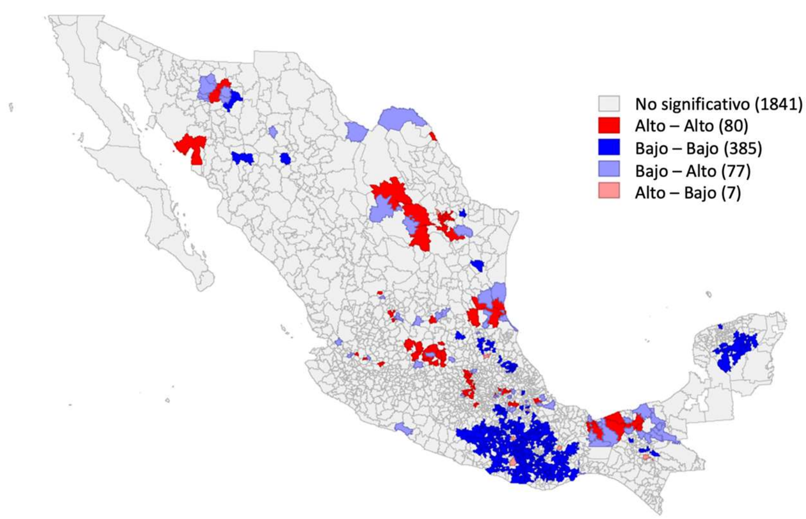
Figure 2. Map of Local Moran's I Index of Remuneration per Worker



Source: Prepared by authors.

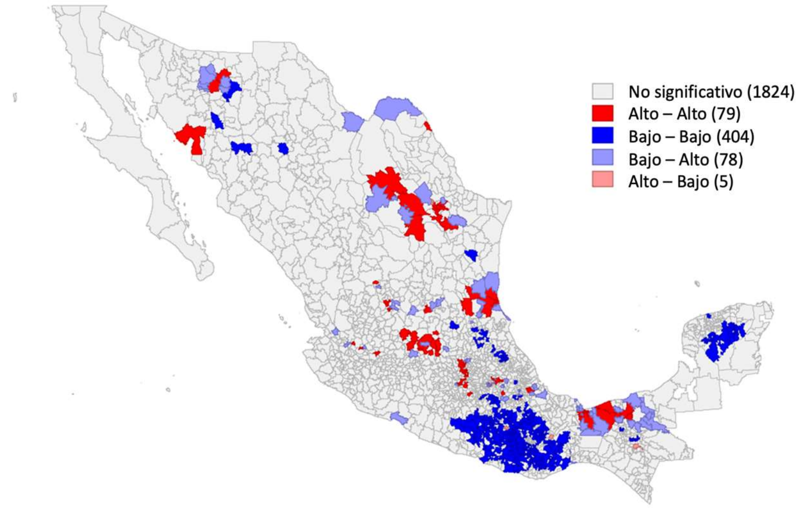
In Figures 3 and 4, it is observed that productivity, calculated by hours worked or by the number of workers, presents clusters in similar regions, coinciding with clusters of low remuneration in the south but with fewer clusters of high-high relationship in the north. That is, although clusters of high remuneration are present in the northern region of the country, there are fewer clusters of high productivity.

Figure 3. Map of Local Moran's I Index of Productivity based on Hours Worked



Source: Prepared by authors.

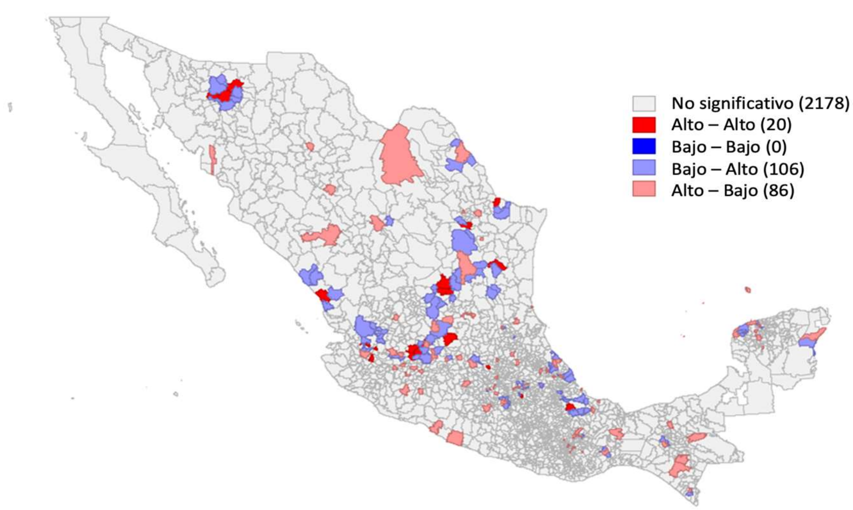
Figure 4. Map of Local Moran's I Index of Productivity based on Number of Workers



Source: Prepared by authors.

Regarding exports, it is the variable that presents the highest number of low-high relationship clusters. That is, municipalities with low levels of exports surrounded by municipalities with high levels of exports in the manufacturing sector. This could be explained by sectoral and regional inequities in exports (see Figure 5).

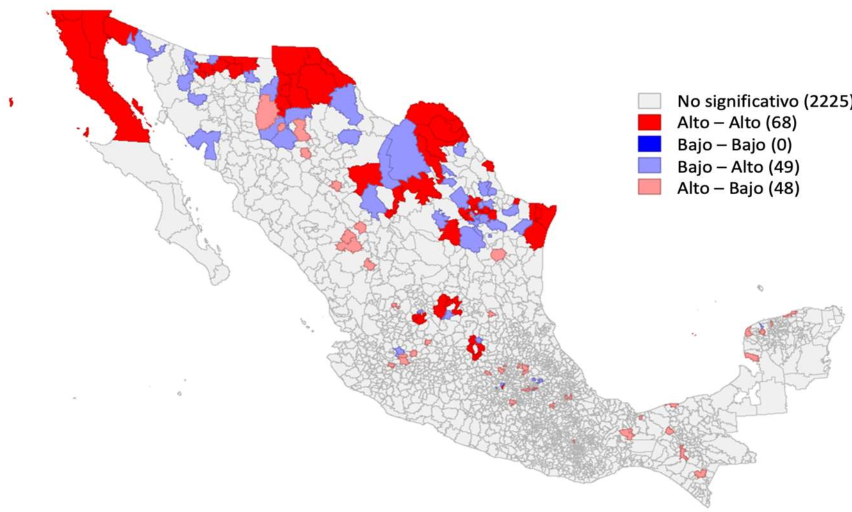
Figure 5. Map of Local Moran's I Index of Exports



Source: Prepared by authors.

In Figure 6, it is observed that Foreign Direct Investment presents high-high type clusters in the northern zone of the country and bordering with the United States. This makes sense because Foreign Direct Investment is calculated as the proportion of foreign capital in manufacturing companies.

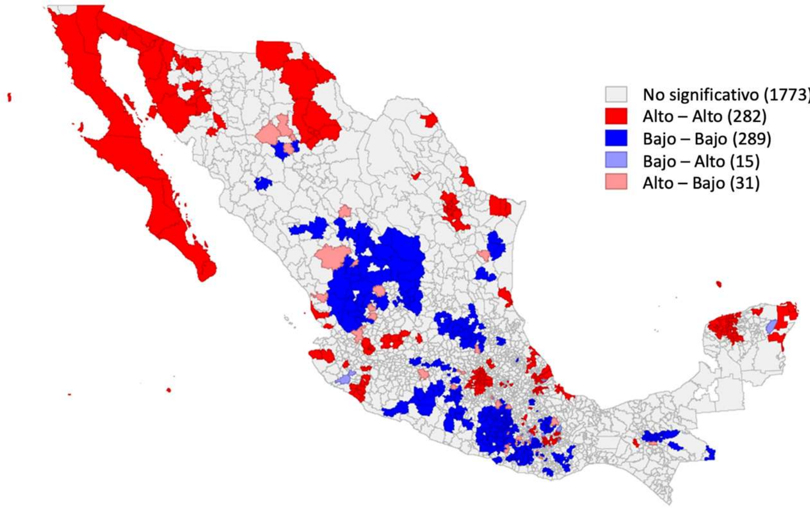
Figure 6. Map of Local Moran's I Index of Foreign Direct Investment



Source: Prepared by authors.

The employment rate also presents high-high relationship clusters in the northern region of the country and in the east (see Figure 7). It is interesting that in the east, clusters of low-low relationship were observed in the variables of remuneration and productivity.

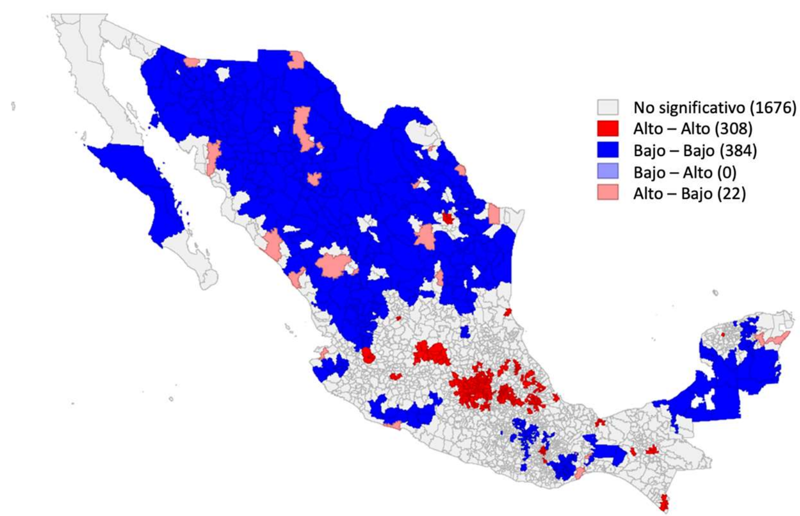
Figure 7. Map of Local Moran's I Index of Employment Rate



Source: Prepared by authors.

Population density is the variable that presents the highest number of clusters (see Figure 8). It is noteworthy that clusters of low relationship are present in the northern and eastern regions of the country, while clusters of high population density are present in the central region of the country.

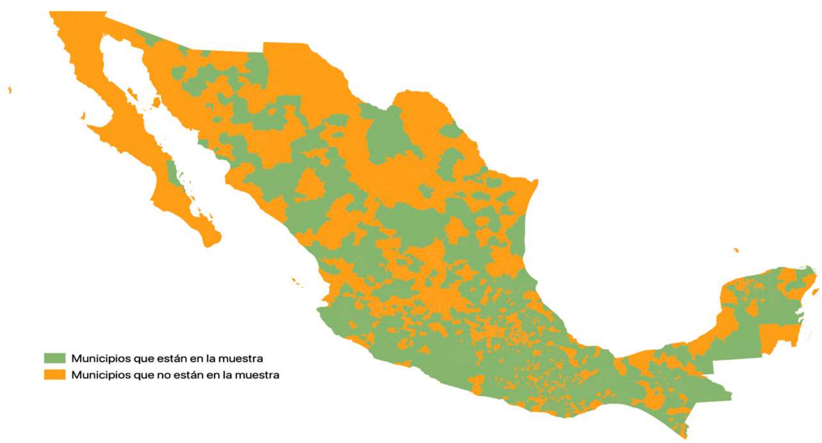
Figure 8. Map of Local Moran's I Index of Population Density



Source: Prepared by authors.

Finally, a limitation of this work is that the variables under analysis are not available for all municipalities. That is, we have a balanced panel. To calculate spatial econometric models, we require balanced panels, so we eliminate municipalities that do not have all the variables for the years under analysis. This means that we have a sample of 67% of the municipalities, that is, 1,636 municipalities in the sample out of a universe of 2,458 municipalities. Figure 9 shows the municipalities that are part of the sample of this research.

Figure 9. Municipalities included and not included in the sample of the empirical models



Source: Prepared by authors.

5. Results

Table 5 presents the results of the empirical model. The first column shows the names of the variables whose coefficients are calculated from columns 2 to 9. The first two models (columns 2 to 5) correspond to the Spatial Durbin Model (SDM) with random effects: the first model considers productivity based on hours worked, and the second considers productivity based on the number of workers. Models 3 and 4 correspond to the SDM with cross-sectional averages (common factors): the third model considers productivity based on hours worked, and the fourth considers productivity based on the number of workers.

In all four models, lagged remunerations show a significant effect. However, in the SDM models with common factors, the relationship is negative. This implies that remunerations from the previous year have a negative effect on remunerations in the current year (t). Policymakers should recognize the persistence of remuneration levels over time. Initiatives aimed at enhancing remuneration in previous periods can have a lasting effect on current remuneration levels. This underscores the importance of implementing policies that promote sustained growth in remunerations to improve overall economic well-being. On the other hand, remunerations from the previous year in neighboring municipalities (a 1% increase) have a positive effect on the productivity of the base municipality in year t (a 0.04% increase).

Productivity has a significant effect on both the remunerations of the base municipality (X) and those of neighboring municipalities (W*X): a 1% increase in productivity results in a 0.77% increase in the remunerations of the base municipality and a 0.08%-0.09% increase in neighboring municipalities. This spatial effect of productivity is not observed in the SDM models with random effects. Notably, the effect with both methods for calculating productivity yields similar coefficients, as observed in the clusters in Figures 3 and 4. On the one hand, Policies targeting improvements in productivity, particularly those focused on increasing efficiency in labor utilization or enhancing technology to boost output per hour worked, can significantly enhance remuneration levels. Investments in training programs, technological innovation, and infrastructure aimed at enhancing labor productivity can yield substantial returns in terms of increased remunerations and overall economic growth. On the other hand, policies aimed at increasing the overall number of workers in the manufacturing sector can contribute to higher productivity levels, which, in turn, can lead to increased remunerations. However, policymakers should also consider the quality of employment generated, ensuring that increases in the number of workers are accompanied by improvements in skill levels, job security, and working conditions to maximize the positive impact on remunerations and economic well-being.

On the other hand, exports do not show a significant effect in any of the models. The employment rate shows a negative relationship with the remunerations of the base municipality but not with the remunerations of neighboring municipalities. Finally, population density exhibits mixed effects: the negative spatial effect (W*X) can be interpreted as economies of scale generated by neighboring municipalities, i.e., an increase in population density of neighboring municipalities leads to a reduction in remunerations (reduction in labor costs). Conversely, the effect on the base municipality (X) is interpreted as agglomeration economies: an increase in population density of the base municipality leads to an increase in remunerations (increase in labor costs). The spatial effect of population density is not observed in the SDM models with random effects.

The presence of spatial effects in the models highlights the interconnectedness and interdependence of neighboring municipalities in terms of economic dynamics. The negative spatial effect observed in some variables, such as lagged remunerations and population density, underscores the role of spatial spillovers in shaping economic outcomes. This implies that policies aimed at enhancing productivity or increasing labor costs in one municipality may have spill-over effects on neighboring areas, influencing their economic performance. Understanding these spatial interdependencies is crucial for policymakers to design targeted interventions that consider both local and regional dynamics.

The findings underscore the importance of considering regional disparities and spatial interactions in the formulation of development policies. While agglomeration economies drive up labor costs in densely populated areas, neighboring municipalities may experience downward pressure on remunerations due to economies of scale. Policymakers need to strike a balance between promoting agglomeration benefits and mitigating negative spillovers to ensure more equitable and sustainable regional development. Moreover, investments in infrastructure, education, and innovation aimed at enhancing productivity should be strategically coordinated across neighboring regions to maximize synergies and minimize disparities.

Table 5. Results[1/4/5/]

	(1)		**-2**		**-3**		**-4**	
	Dependent variable: Remunerations							
	Dynamic spatial Durbin model with random effects				**Dynamic spatial Durbin model with cross-sectional averages**			
Variable	**X**	**W*X**	**X**	**W*X**	**X**	**W*X**	**X**	**W*X**
Remunerations (t-1)	0.332***	0.0513**	0.314***	0.0507**	-0.219***	0.0388*	-0.216***	0.0422*
	-16.82	-3	-16.01	-2.99	(-18.04)	-2.06	(-17.93)	-2.26
Productivity based on hours worked	0.962***	0.0227			0.766***	0.0954*		
	-29.52	-0.52			-29.22	-2.31		
Productivity based on workers			0.931***	0.0112			0.747***	0.0782*
			-31.56	-0.27			-30.91	-2.03
Exportations	-0.741	-0.386	-0.775	-0.384	0.659	-0.361	0.629	-0.381
	(-1.08)	(-0.52)	(-1.11)	(-0.53)	-1.27	(-0.54)	-1.23	(-0.57)
Ocupation	-0.545	-1.905	-0.508	-1.673	-3.168***	-1.791	-2.975***	-1.64
	(-0.65)	(-1.85)	(-0.60)	(-1.66)	(-3.80)	(-1.50)	(-3.60)	(-1.38)
Population density	0.108***	0.00479	0.0933**	0.00121	0.468*	-1.117**	0.476*	-1.068**
	-3.32	-0.12	-2.89	-0.03	-2.01	(-2.72)	-2.06	(-2.62)
Intercept	38.89**		34.08**					
	-3.09		-2.77					
Spatial effect	0.00171		0.00169		-0.0103		-0.00895	

	-0.13	-0.13	(-0.64)	(-0.55)
Sample	1636	1636	1636	1636
CD test[2/]	0	0		
Baltagi 2003 test[3/]	0	0		
Years	3	3	3	3
Control Variables	Sí	Sí	Sí	Sí
W Matrix	Queen contiguity	Queen contiguity	Queen contiguity	Queen contiguity

Source: Prepared by authors.

Notes: 1/ t-statistics are in parentheses.

2/ CD test and Baltagi (2003) test p-values are reported. The CD test, or the Cliff-Ord test, assesses spatial autocorrelation in panel data models. The null hypothesis for this test is that there is no spatial correlation among the residuals. A p-value greater than the chosen significance level (e.g., 0.05) fails to reject the null hypothesis, suggesting no spatial autocorrelation among the residuals.

3/ The Baltagi (2003) test evaluates the presence of spatial autocorrelation in panel data models with fixed effects. The null hypothesis for this test is also that there is no spatial correlation among the residuals.)

4/ Statistical significance p-value levels: *p<0.05, **p<0.01, *p<0.001.

5/ Robustness tests were conducted: Models with spatial weight matrix by proximity k=1,2,3,4,7, and age groups were substituted according to the OIT - ILOSTAT classification. The coefficients and significance levels remained the same with these robustness tests.

6. Conclusions and Policy Recommendations

This research provides important results that can serve as valuable tools for public policy. Firstly, the heatmaps produced with the Local Moran's Index are useful for identifying significant hotspots of various variables, identifying clusters of high (high-high), low (low-low), and mixed (high-low and low-high) values. Additionally, the results of the spatial econometric models show a spatial relationship between remunerations, productivity, and population density in the manufacturing sector of municipalities in Mexico, as identified in González, López, and Cabral (2022) at the state level. This suggests that public policies aimed at increasing productivity in municipalities could have spill-over effects on neighboring municipalities. For example, developing policies promoting regional cooperation to maximize positive spillovers effects from high to low clusters. Also, targeting investment in training, education and R&D - aimed to develop regional hubs- could boost spillovers effects and diminish regional economic disparities.

Furthermore, this research contributes to the literature on spatial econometric models with common factors using cross-sectional averages instead of space-time effects. It was demonstrated that the relationship between the variables under study can be better calculated with spatial models with common factors due to the heterogeneity of municipal characteristics. Also, this work contributes to the literature on cross-sectional dependence models by extending the analysis beyond traditional econometric approaches and incorporating spatial dynamics into the modeling framework. By employing Spatial Durbin Models (SDMs) with both random effects and cross-sectional averages, the study addresses the limitations of conventional cross-sectional models that overlook spatial interdependencies among observations. This approach allows for a more comprehensive understanding of the spatial processes underlying economic phenomena, which is crucial for capturing complex real-world dynamics.

Moreover, the inclusion of spatial effects in the analysis sheds light on the spatial spillovers and interdependencies that exist among neighboring municipalities. This adds a layer of depth to the analysis by acknowledging that economic outcomes in one region can be influenced by the characteristics and behaviors of adjacent areas. By explicitly modeling these spatial relationships, the study not only improves the accuracy of the estimation but also provides valuable insights into the mechanisms driving regional economic dynamics.

Furthermore, by comparing the performance of SDMs with different specifications (random effects vs. cross-sectional averages), the study contributes to methodological advancements in spatial econometrics. It evaluates the relative merits of each approach in capturing spatial dependencies and provides guidance on the selection of appropriate modeling strategies based on the data characteristics and research objectives. This methodological contribution enhances the toolkit available to researchers studying cross-sectional dependence, thereby advancing the state of the art in spatial econometric modeling.

Building on these results, future research could explore additional factors that influence spatial economic dynamics, such as geographical features, transportation networks, and institutional frameworks. Furthermore, investigating the temporal dynamics of spatial effects over different time horizons could provide insights into the long-term sustainability of regional development initiatives. Additionally, integrating qualitative methods, such as case studies or stakeholder interviews, could offer deeper contextual understanding of the mechanisms driving spatial interactions and help identify policy levers for fostering inclusive and resilient regional economies. Overall, advancing our understanding of spatial econometric modeling can provide valuable insights for designing more effective and targeted policies to promote balanced and sustainable regional development.

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