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Article

Spatial Dependence in the Cyclical Sensitivity of Labour Supply: An Analysis at the Regional Level in Ecuador

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Abstract: The labour supply has historically been subject to influence from the economic cycle. On the other hand, there is a paucity of research in the Latin American region examining the impact of social factors on labour participation in diverse contexts. This study examines the spatial dependence of the cyclical sensitivity of labour supply in 23 provinces of Ecuador. A time series analysis was conducted to calculate the cyclical sensitivities of labour supply, and spatial econometric techniques were applied to assess spatial dependence using monthly data for the period 2021 to 2024. We found evidence of a positive and significant spatial dependence in the cyclical sensitivity of labour supply. Our findings suggest that labour decisions in one province are influenced by those in neighbouring provinces, thereby providing a framework for the design of public policies that take into account these interdependencies.

Keywords: added worker effect; discouraged worker effect; bandwagon worker effect; labour participation rate; spatial dependence; business cycle

JEL Classification: C23; D03; E32; J21; R23



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1. Introduction

Historically, labour supply has been conditioned by fluctuations in the business cycle. Since the publication of seminal studies such as those by Woytinsky (1940) and Long (1953), certain patterns in the labour market have been observed as a result of this interrelationship, giving rise to the classic added worker and discouraged worker effects (i.e., AWE and DWE, respectively). The economic literature has devoted considerable attention to these effects. However, research on the possible influence of social factors is comparatively limited. The aim of this paper is to contribute to the existing body of knowledge on this topic.

A study by Martín-Román et al. (2020) illustrates that, as labour supply is a demand for leisure, the well-known microeconomic theory of the bandwagon effect (Leibenstein 1950), which refers to the demand for products, can be applied to comprehend specific labour market dynamics. Consequently, these authors integrate social effects as a significant factor influencing labour supply decisions. Furthermore, these social effects can be examined through the use of spatial econometric techniques, as demonstrated by Halleck-Vega and Elhorst (2017); Fogli and Veldkamp (2011).

Martín-Román et al. (2020) developed a conceptual framework linking social effects with cyclical labour market dynamics. Using estimates of the cyclical sensitivity of labour supply in 50 Spanish provinces, they formulated and validated the bandwagon worker effect (BWE) hypothesis. This hypothesis describes how an individual's job search decisions are influenced by the decisions of their environment, generating a positive spatial

dependence in which the labour participation rates of one region are influenced by the participation rates of neighbouring regions.

Despite these advancements, the application of the BWE theory has been largely confined to developed economies, leaving a gap in understanding how these social dynamics operate in different geographical and economic contexts, particularly in Latin America. Addressing this gap, the present study aims to explore the spatial dependence in the cyclical sensitivity of labour supply across the provinces of Ecuador. Specifically, we investigate the role of social influences in shaping labour supply decisions and how these influences manifest spatially within the country.

By examining whether labour participation rates in one province are affected by those in neighbouring provinces, this research contributes to a more comprehensive understanding of regional interdependencies in labour markets. Additionally, we consider how the influence of neighbouring provinces changes as the concept of “neighbourhood” is expanded to include more distant regions, providing insights into the spatial reach of social effects on labour supply.

In terms of methodology, we employed a time series approach to calculate the cyclical sensitivities of labour supply for each of Ecuador’s 23 provinces between 2021 and 2024, utilising monthly data. This enables the subsequent application of spatial econometric techniques to analyse the spatial dependencies under investigation. The combination of these methodologies allows us to test the central premise of our research regarding the presence and extent of spatial dependence in labour supply sensitivities.

The principal contribution of this study lies in extending the application of the BWE theory to a Latin American context, offering a novel perspective on the spatial dynamics of the labour market in Ecuador. The findings are expected to provide valuable insights for policymakers, particularly in the design of public policies that account for regional interdependencies and social influences on labour supply decisions.

The remainder of this paper comprises five sections. Section 2 presents a review of the existing literature on the subject. Section 3 provides a detailed account of the data to be utilised, the provinces under investigation, the timeframes subjected to analysis, and the characteristics of the series employed for modelling purposes. Section 4 outlines the methodology employed. The findings are presented in Section 5. Finally, Section 6 presents the conclusions and economic policy recommendations associated with the results of the research.

2. Background

2.1. Foundations and Evidence on the AWE and DWE

It is of paramount importance for policymakers to analyse the dynamics of labour supply and its response over the business cycle, as this allows them to anticipate and mitigate phenomena that could affect the labour market. In particular, the economic literature highlights the AWE and DWE hypotheses as means of exploring these relationships.

The seminal research of [Woytinsky \(1940\)](#) has established that the AWE may cause an overestimation of the unemployment rate in times of recession. This is because more people tend to enter the labour force to look for work and compensate for the loss of household income when the head of the household loses their job. Conversely, during periods of economic growth, the author posits that the unemployment rate may be underestimated.

In relation to the DWE, [Long \(1953, 1958\)](#) posits that, when employment prospects are limited, some workers exit the labour market and become inactive. This effect is reversed when employment prospects become more favourable. Consequently, there is an increase in the number of individuals willing to offer their labour in the labour market. Accordingly, this perspective would lead to an underestimation of the unemployment rate during periods of economic expansion and an overestimation during recessions.

More contemporary studies, such as that conducted by [Martín-Román \(2022\)](#), suggest that, in the event of DWE prevailing over AWE, labour participation is pro-cyclical;

otherwise, it is counter-cyclical. While these hypotheses have been the subject of study throughout history, there is no general consensus as to which of the two effects is dominant.

In developed countries, research in favour of the AWE includes the studies conducted by [Başlevent and Onaran \(2003\)](#), [Congregado et al. \(2014\)](#), [Gałecka-Burdziak and Pater \(2016\)](#), and [Bredtmann et al. \(2017\)](#). Conversely, studies substantiating the existence of the DWE encompass those conducted by [Lee and Cho \(2005\)](#), [Lee and Parasnis \(2014\)](#), [Rodríguez-Modroño et al. \(2015\)](#), [Evans \(2018\)](#), and [Paternesi Meloni \(2024\)](#). In Latin America, research conducted by [Cerrutti \(2000\)](#), [Fernandes and De Felício \(2005\)](#), [Hernández and Romano \(2011\)](#), [Cardona-Sosa et al. \(2018\)](#), [Ontaneda et al. \(2022\)](#), and [Maridueña-Larrea and Martín-Román \(2024\)](#) has tended to support the concept of the AWE. However, [Paz \(2009\)](#) and [Gonzaga and Reis \(2011\)](#) present evidence in favour of the DWE.

Although in Latin America there is evidence from studies addressing the AWE and DWE effects, it should be noted that the majority of these studies focus on Argentina and Brazil, which makes their reach comparatively limited in scope and depth when compared to that of developed countries. For decades, discussions on these effects have been extensively conducted in advanced economies. However, in Latin America, there is still a paucity of empirical evidence to clearly characterise the prevalence and dynamics of AWE and DWE in the region.

2.2. Influence of Geographical Space on Labour Participation Decisions

The significance of grasping these effects within the Latin American context is further underscored when we take into account the social repercussions and spatial interdependence of labour markets, which are pivotal in comprehending how labour engagement responds to the business cycle. In the region, [Rodríguez \(2021\)](#) found that the labour participation of young people in Colombia is significantly influenced by the similar decisions of their neighbours, with variations by gender. By incorporating geographical analysis through GPS location data, the author demonstrated how spatial proximity affects labour participation decisions. Factors such as education, household income and labour informality are of pivotal importance in this regard.

In alignment with this perspective, [Dietz \(2002\)](#) underscores the significance of geographic and social proximity in shaping economic and occupational outcomes. Similarly, [Andrews et al. \(2004\)](#) investigate the impact of neighbourhood composition and the quality of the residential environment on the employment outcomes of young people in Australia. Their findings indicate that individuals who grow up in low-quality neighbourhoods are more likely to experience unemployment. In Germany, [Möller and Aldashev \(2007\)](#) provided a more nuanced understanding of the relationship between wage dispersion, regional economic conditions and labour participation. Their approach was based on a theoretical and empirical investigation utilising spatial econometrics.

[Dubrovskaya and Kozonogova \(2021\)](#) highlight that inter-territorial spatial relations in Russia have a significant impact on labour demand, underlining the need to consider spatial effects when modelling the dynamics of employment indicators. Geographical space, according to [Hesse and Scheiner \(2007\)](#), and regional socio-demographic composition, according to [Lerbs and Oberst \(2014\)](#), are influential variables in individuals' choice of place of residence, especially in more specialised labour markets, as they seek to improve their family environment.

This research highlights the importance of incorporating the spatial dimension in the analysis of labour markets in order to develop more effective policies, as evidenced by studies such as those by [Falk and Leoni \(2010\)](#), [Liu and Noback \(2011\)](#), and [Kawabata and Abe \(2018\)](#). However, one of the most important contributions of this paper is the incorporation of social effects (which have been shown to influence various economic outcomes) to explain cyclical fluctuations in labour supply in Ecuador. Using spatial econometric techniques at the regional level, we aim to validate the BWE, which describes how an individual's job search decisions are influenced by the decisions of his or her environment. The logic of the BWE is based on the fact that labour supply is a demand for

leisure. In this way, the concept of the bandwagon effect developed by [Leibenstein \(1950\)](#) can be extended to the study of the labour market.

2.3. Spatial and Social Dynamics in Labour Participation

The literature refers to the influence of social group behaviour on individual decisions as social effects. Sociology has also been concerned with identifying the mechanisms by which a neighbourhood effect can arise and operate. [Akerlof \(1980\)](#) highlights the importance of social norms in individual decision-making, arguing that these norms can strongly influence people's behaviour, even when following them is costly at the personal level. Consistently, subsequent studies, such as those by [Rüger and Viry \(2017\)](#) and [Eismann et al. \(2019\)](#), confirm that social norms, as well as environmental and interdependence theories, significantly influence individual spatial mobility decisions in the work environment.

From a financial or managerial perspective, it has been confirmed by [Scharfstein and Stein \(1990\)](#) and [Welch \(1992\)](#) that, at the individual level, the investment decisions of others are imitated. Although this behaviour is inefficient from a social point of view, it may be rational from the perspective of individuals concerned about their reputation in their area of involvement. Therefore, the decision rules chosen by individuals will be characterised by aggregate behaviour, i.e., people will do what others do rather than use their own information ([Banerjee 1992](#); [Bikhchandani et al. 1992](#); [Duflo and Saez 2002](#); [Rosen et al. 2002](#)).

The literature reviewed strongly supports the idea that social influences and geographical conditions can play a crucial role in the decision to participate in the labour market. From seminal to more recent studies, there is a consensus on the significant influence of observed behaviour on individual decision-making. These findings suggest that social interactions and geographical proximity should be key elements in any labour market analysis.

This paper highlights the importance of considering social and spatial effects when analysing labour market dynamics. This not only provides a deeper understanding of the factors influencing labour market participation, but also a solid basis for future research in this area. It also provides a valuable opportunity to contribute to the Latin American literature on AWE and DWE. There are no similar studies in the region that have taken this approach, combining micro- and macroeconomic criteria with spatial econometrics. The resulting findings may suggest effective policy tools to strengthen the dynamics of labour markets.

3. Data

3.1. Descriptive Analysis

The study covers the period from January 2021 to April 2024¹, with monthly frequency data, totalling 40 observations for each province. The datasets were obtained from Ecuador's National Institute of Statistics and Census (INEC; by its acronym in Spanish) by tabulating microdata from the National Employment, Unemployment and Underemployment Survey (ENEMDU; referred to in Spanish as ENEMDU). For each of the country's 23² provinces, we extracted the labour force participation rate and the unemployment rate, weighted at the national level using the expansion factor provided by INEC³, according to the following definitions:

$$\text{Labour force participation rate (LFPR)} = \frac{\text{Labour force}}{\text{Working age population}} \quad (1)$$

$$\text{Unemployment rate (UR)} = \frac{\text{Unemployed population}}{\text{Labour force}} \quad (2)$$

Table 1 shows some descriptive statistics for the variables studied in this research. The Amazonian provinces of Napo and Orellana have the highest participation rates, with averages of 88.16% and 88.21%, respectively. The standard deviations in these provinces are relatively low, 4.60% in Napo and 3.53% in Orellana, indicating a stable participation

rate in the area analysed. On the other hand, provinces such as Esmeraldas and Santa Elena have lower participation rates, with averages of 57.33% and 56.21% and standard deviations of 2.78% and 3.54%, respectively.

Table 1. Descriptive statistics (Jan-21 to Apr-24; in %).

Province	LFPR				UR			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Azuay	71.28	2.66	65.80	77.30	3.63	1.24	1.57	6.88
Bolivar	64.54	4.83	53.84	77.32	1.06	0.89	0.08	3.61
Carchi	63.44	3.96	57.96	72.20	5.64	1.68	2.33	11.00
Cañar	71.88	5.46	59.27	82.36	3.79	1.65	1.13	9.14
Chimborazo	81.84	3.65	73.18	89.96	2.26	1.53	0.18	8.46
Cotopaxi	84.05	4.50	74.33	92.10	2.24	1.16	0.63	5.25
El Oro	65.72	1.96	61.58	69.70	6.15	1.60	3.45	10.82
Esmeraldas	57.33	2.78	52.10	63.75	9.60	2.32	6.41	16.91
Guayas	60.77	2.63	55.66	67.20	3.56	1.02	1.90	7.08
Imbabura	62.94	2.77	56.71	68.54	6.35	1.52	3.28	9.16
Loja	70.40	3.44	63.70	77.61	3.85	1.01	1.90	6.51
Los Rios	59.86	3.85	51.38	67.79	2.18	1.27	0.23	5.56
Manabí	58.50	4.05	51.86	68.22	2.40	1.26	0.57	4.72
Morona Santiago	84.03	5.97	66.25	92.73	1.22	1.14	0.09	4.46
Napo	88.16	4.60	78.08	95.27	1.58	1.00	0.35	4.18
Orellana	88.21	3.53	78.37	95.39	2.08	1.48	0.31	6.37
Pastaza	87.47	5.12	75.90	94.73	1.94	1.24	0.17	5.18
Pichincha	63.29	1.84	59.20	67.44	8.88	2.04	5.89	14.48
Santa Elena	56.21	3.54	50.22	63.78	3.05	1.29	0.60	6.01
Santo Domingo	62.03	4.73	48.05	70.02	2.53	1.71	0.30	9.02
Sucumbíos	66.79	6.22	55.80	81.63	5.04	2.28	0.91	11.11
Tungurahua	80.30	2.37	75.56	84.06	2.42	0.84	0.83	4.48
Zamora Chinchipe	74.56	4.82	61.91	84.13	3.02	1.37	1.18	7.93
Total	70.59	11.29	48.05	95.39	3.67	2.67	0.08	16.91

In terms of unemployment, Esmeraldas and Pichincha stand out as having the highest rates. Esmeraldas has an average of 9.60%, with a standard deviation of 2.32%, reflecting significant monthly variations. Pichincha, on the other hand, has an average of 8.88% and a standard deviation of 2.04%, also showing fluctuations in unemployment levels throughout the period analysed. Bolívar and Morona Santiago, on the other hand, have lower average unemployment rates of 1.06% and 1.22%, with standard deviations of 0.89% and 1.14%, respectively.

The overall analysis shows that the national mean for LFPR is 70.59% with a standard deviation of 11.29%, while the national mean for UR is 3.67% with a standard deviation of 2.67%. The variability observed between provinces, such as in Sucumbíos, with standard deviations of 6.22% for LFPR and 2.28% for UR, suggests significant differences in participation and unemployment at the regional level. These data highlight the diversity of the labour market in Ecuador, with each province showing different patterns of participation and unemployment.

By way of geographical illustration⁴, Figure 1 shows the level of the participation rate and the unemployment rate for each of the 23 provinces of the country. In general, and as a complement to the figures presented above, there are areas where certain trends are accentuated (e.g., the North, the East, the South-West, among others). This could anticipate a possible spatial correlation that influences the decision to participate in the labour market in the provinces of Ecuador. The observed concentrations could be influenced by region-specific economic, social, and structural factors. These initial patterns provide a basis for the spatial econometric analysis to be carried out in the study, allowing for a deeper understanding of labour dynamics at the regional level in Ecuador.

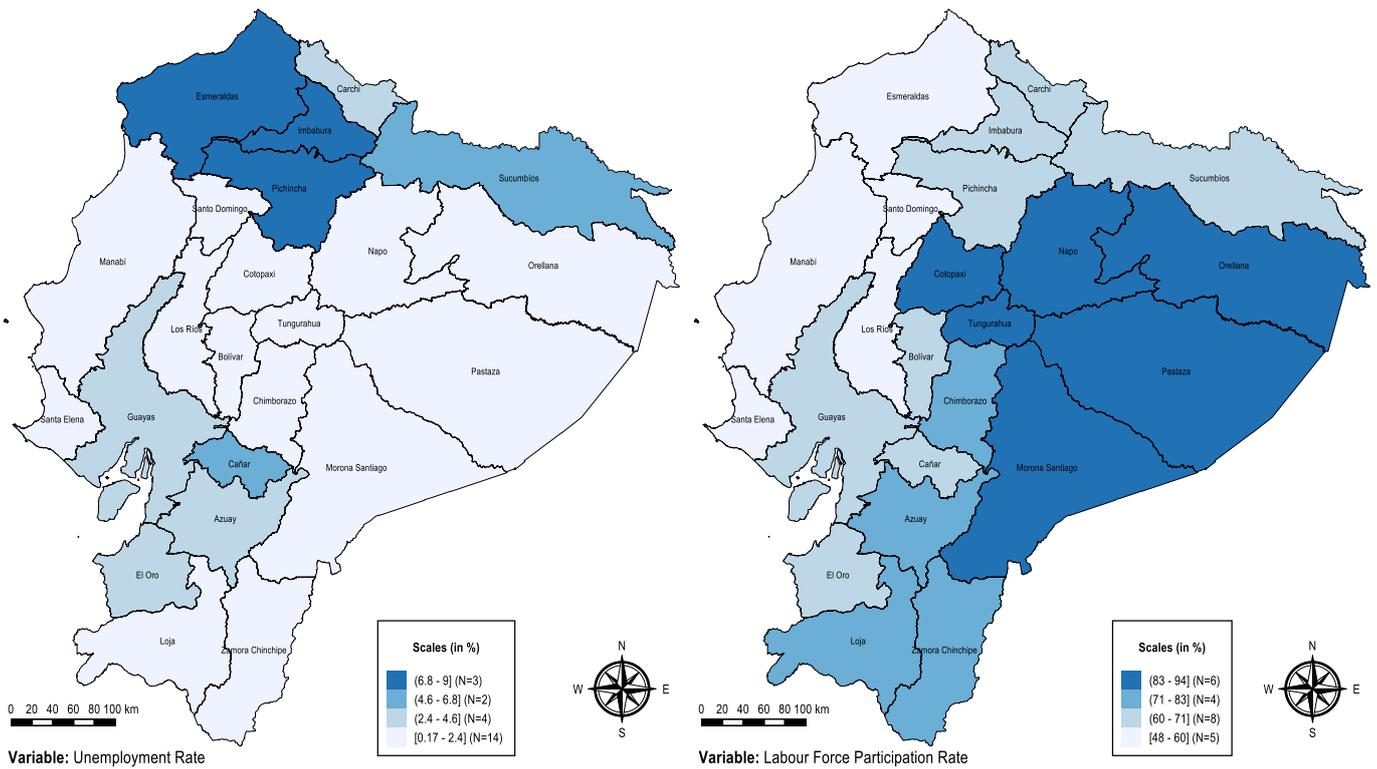


Figure 1. Regional Labour Indicators (April 2024). Source: ENEMDU–INEC. Own elaboration.

3.2. Series to Be Used

This research focuses on the analysis of the cyclical component of the labour force participation rate and the unemployment rate for each province in order to investigate the spatial dependence of the cyclical sensitivity of regional labour supply in Ecuador. Kaiser and Maravall (1999) argue that time series often contain long-term trends that may mask cyclical fluctuations. By accounting for the cyclical component, we expect to obtain stationary series, which are essential for accurate econometric analysis, providing a clearer picture of cyclical dynamics and avoiding the estimation of spurious correlations.

Much of the economic literature suggests the use of the Hodrick and Prescott (1997) filter (HP) to extract the cyclical residual from a time series. Given a series of observations y_t ($t = 1, 2, \dots, T$) in a time series, Mise et al. (2005) state that the HP filter is an additive decomposition of $y_t = y_t^g + y_t^c$.

y_t^g is identified as the trend component and y_t^c as the cyclical component. According to the authors, the trend component y_t^g is estimated by solving the following minimisation problem:

$$\min_{\{y_t^g\}} \left\{ \sum_{t=1}^T (y_t - y_t^g)^2 + \lambda \sum_{t=2}^{T-1} [(y_{t+1}^g - y_t^g) - (y_t^g - y_{t-1}^g)]^2 \right\}$$

where

- $\sum_{t=1}^T (y_t - y_t^g)^2$ measures the discrepancy between y_t^g and y_t .
- $\lambda \sum_{t=2}^{T-1} [(y_{t+1}^g - y_t^g) - (y_t^g - y_{t-1}^g)]^2$ imposes a penalty for lack of smoothness in the trend series.
- λ is the parameter that determines the degree of trend smoothing.

Hodrick and Prescott (1997) suggest that the parameter λ should be equal to 1600 for quarterly data. However, when working with monthly data in this research, we will follow the methodology proposed by Backus and Kehoe (1992), who recommend adjusting the

value of 1600 by the square of the frequency of the observations relative to the quarterly data. Thus, for monthly data, the relative frequency would be 3 and the parameter λ would be 14,400. Based on this specification, we proceeded to extract the cyclical residual of the series in levels. Figures 2 and 3 show its evolution for the unemployment and labour force participation rates, respectively, for the 23 provinces of Ecuador.

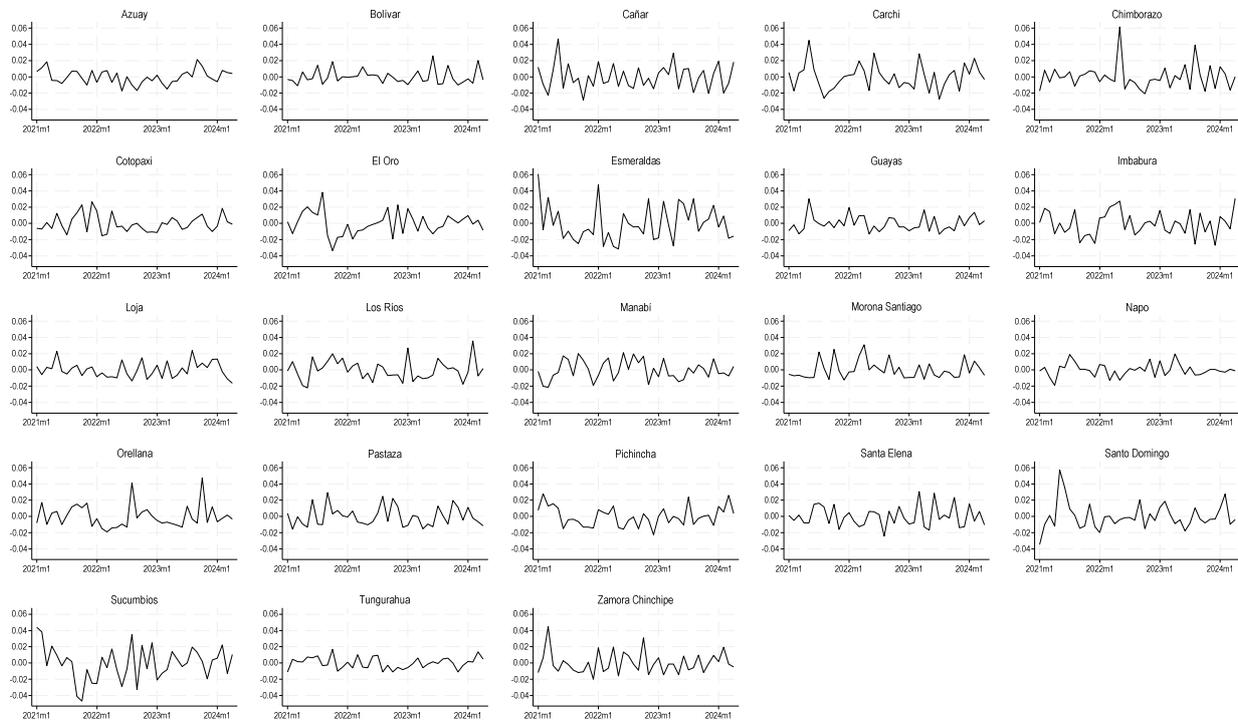


Figure 2. Cycle of the unemployment rate by province (HP $\lambda = 14,400$). Source: ENEMDU–INEC. Own elaboration.

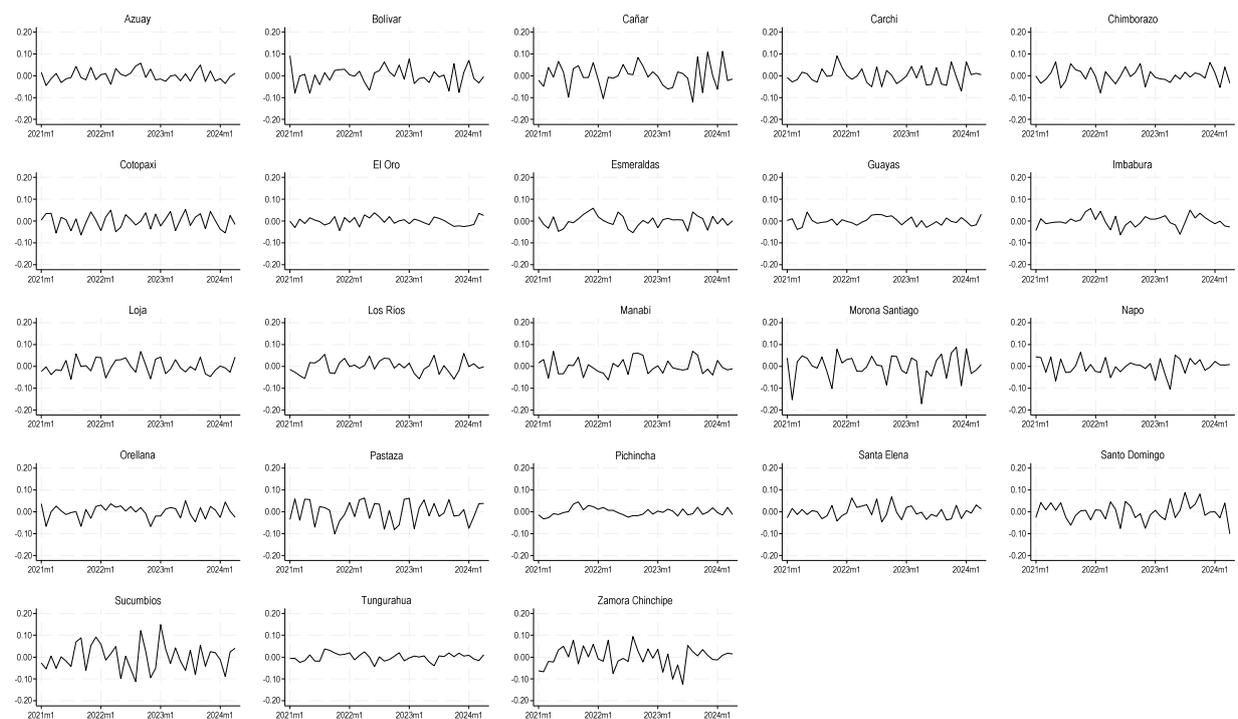


Figure 3. Cycle of the labour force participation rate by province (HP $\lambda = 14,400$). Source: ENEMDU–INEC. Own elaboration.

3.3. Series Properties

In order to obtain the cyclical sensitivities of provincial labour supply, the variables are modelled on the basis of their cyclical residuals. This will allow the short-run sensitivities in the relationship between the LFPR cycle and the UR cycle to be captured for each region. However, given the nature of the time series variables to be used, [Leslie et al. \(1995\)](#) stress the importance of checking their stationarity to avoid spurious correlations in the regressions. The presence of unit roots in the time series can lead to incorrect inferences and the estimation of relationships that are not true. Therefore, it is crucial to use unit root tests to ensure that the series are stationary in order to obtain reliable results.

Based on the characterisation of each time series, different unit root tests were applied. In addition to the conventional Augmented Dickey–Fuller (ADF) unit root test, the Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are included in [Table 2](#). The purpose of these tests is to increase the robustness of the results.

Table 2. Unit root test.

Province	Cycle of Variables	ADF	PP	KPSS
		(H0: Unit Root)	(H0: Unit Root)	(H0: Stationarity)
Azuay	LFPR	−6.778 ***	−6.754 ***	0.101
	UR	−4.665 ***	−4.668 ***	0.138
Bolívar	LFPR	−8.701 ***	−8.423 ***	0.050
	UR	−8.011 ***	−8.303 ***	0.063
Cañar	LFPR	−7.833 ***	−7.898 ***	0.035
	UR	−8.162 ***	−8.364 ***	0.029
Carchi	LFPR	−7.467 ***	−7.634 ***	0.043
	UR	−5.566 ***	−5.555 ***	0.051
Chimborazo	LFPR	−7.626 ***	−7.849 ***	0.027
	UR	−8.495 ***	−8.493 ***	0.033
Cotopaxi	LFPR	−8.223 ***	−8.911 ***	0.036
	UR	−5.734 ***	−5.718 ***	0.088
El Oro	LFPR	−5.883 ***	−5.922 ***	0.088
	UR	−5.315 ***	−5.392 ***	0.068
Esmeraldas	LFPR	−5.213 ***	−5.207 ***	0.062
	UR	−7.545 ***	−7.444 ***	0.117
Guayas	LFPR	−5.095 ***	−5.078 ***	0.084
	UR	−6.724 ***	−6.744 ***	0.061
Imbabura	LFPR	−5.002 ***	−5.084 ***	0.052
	UR	−6.092 ***	−6.175 ***	0.051
Loja	LFPR	−7.368 ***	−7.689 ***	0.089
	UR	−5.956 ***	−5.956 ***	0.093
Los Ríos	LFPR	−5.089 ***	−5.017 ***	0.094
	UR	−6.279 ***	−6.286 ***	0.069
Manabí	LFPR	−6.797 ***	−6.857 ***	0.047
	UR	−5.512 ***	−5.489 ***	0.094
Morona Santiago	LFPR	−7.836 ***	−8.142 ***	0.029
	UR	−6.173 ***	−6.175 ***	0.102

Table 2. Cont.

Province	Cycle of Variables	ADF	PP	KPSS
		(H0: Unit Root)	(H0: Unit Root)	(H0: Stationarity)
Napó	LFPR	−8.751 ***	−9.027 ***	0.059
	UR	−5.924 ***	−5.925 ***	0.049
Orellana	LFPR	−7.114 ***	−7.051 ***	0.053
	UR	−6.398 ***	−6.427 ***	0.055
Pastaza	LFPR	−6.988 ***	−7.064 ***	0.029
	UR	−6.301 ***	−6.303 ***	0.048
Pichincha	LFPR	−3.949 ***	−4.007 ***	0.073
	UR	−5.097 ***	−5.115 ***	0.15
Santa Elena	LFPR	−7.088 ***	−7.077 ***	0.087
	UR	−8.296 ***	−9.086 ***	0.031
Santo Domingo	LFPR	−6.416 ***	−6.469 ***	0.072
	UR	−5.368 ***	−5.357 ***	0.044
Sucumbíos	LFPR	−6.901 ***	−7.046 ***	0.046
	UR	−5.801 ***	−5.802 ***	0.111
Tungurahua	LFPR	−4.985 ***	−4.942 ***	0.069
	UR	−6.195 ***	−6.194 ***	0.112
Zamora Chinchipe	LFPR	−6.689 ***	−6.663 ***	0.074
	UR	−8.085 ***	−8.020 ***	0.039

Notes: The ADF and PP tests are based on the critical values of [Mackinnon \(1994\)](#). The KPSS test is based on the KPSS critical values. H0 = null hypothesis. *** indicate that the null hypothesis is rejected at the 1% levels. Figures without * indicate that the null hypothesis is accepted, at least at the 1%, 5%, or 10% levels. The ADF and PP tests were applied without constant or trend, while the KPSS contains at least one constant.

As expected, all series were found to be stationary. In general, we assume that the LFPR and UR cycles are integrated at zero order. Based on these findings, the calculation of the cyclical sensitivity of labour supply for each of Ecuador's provinces would confirm the stationarity of the disturbance or error in their models, thus reflecting robust and non-spurious relationships in the short run.

4. Theoretical Framework and Methodology

4.1. Theoretical Framework

Decisions to participate in the labour market depend not only on individual determinants but also on an individual's environment (e.g., neighbours, social effects, geography, etc.). According to this approach, the participation rate of neighbouring areas and all other areas would also be mutually influenced. This mechanism would lead to an overall spatial dependence. That is, the effects associated with what has been defined as BWE would operate.

[Martín-Román et al. \(2020\)](#) establish a theoretical framework to formalise the BWE, considering the effects of unemployment and linking this effect to a well-established procedure in spatial analysis through Morán's global I. The authors introduce the BWE into labour supply decisions by testing whether the cyclical pattern of the labour share of a given area is positively related to the cyclical pattern of the labour shares of neighbouring areas. Mathematically, a participation rate (PR) function is posited, which can be summarised by Equation (3).

$$PR = f\left(w, w_M^R\left(y(Z), p(Z), PR^N(Z)\right)\right) \quad (3)$$

In expression (3), it is specified that the labour activity depends on two arguments, the real market wage (w) and the reserve wage of the median worker (w_M^R). This second argument is key and, in turn, depends on three factors: real non-labour income (y), the probability of finding a job (p), and the labour participation of what we might call the environment or “neighbourhood” (PR^N). In addition, these three determinants depend on the business cycle (Z).

The idea behind this modelling is that real non-labour income synthesises the theoretical channel through which the AWE operates, the probability of finding a job determines the channel through which the DWE operates, and the labour participation of the environment or neighbourhood determines the channel that synthesises the BWE. From the microeconomic foundations that underpin the model, we obtain the expression (4).

$$\frac{\partial PR}{\partial Z} = \underbrace{\frac{\partial PR}{\partial w_M^R}}_{(-)} \left(\underbrace{\frac{\partial w_M^R}{\partial y} \times \frac{\partial y}{\partial Z}}_{AWE(+)} + \underbrace{\frac{\partial w_M^R}{\partial p} \times \frac{\partial p}{\partial Z}}_{DWE(-)} + \underbrace{\frac{\partial w_M^R}{\partial PR^N} \times \frac{\partial PR^N}{\partial Z}}_{BWE(?)} \right) = \beta^+ \gtrless 0 \quad (4)$$

The economic intuition behind derivatives is simple. It follows from the very concept of the reservation wage that, as the reservation wage increases, the PR decreases and vice versa. When non-labour income increases, there is an income effect that increases the reservation wage and vice versa. Moreover, it is logical to assume that non-labour income is pro-cyclical. Taken together, this leads to a conventional AWE that causes counter-cyclical movements in the PR. On the other hand, when the probability of finding a job increases, the reservation wage decreases and vice versa. It is also assumed that the probability of finding a job is pro-cyclical. Overall, the DWE would lead to the usual pro-cyclical pattern of the PR.

However, the most interesting term in expression (4) is the one related to BWE. The type of social effect considered in this research would imply that, if labour participation in the environment increases, it should also increase in the benchmark province. This would imply a clearly negative sign of the derivative of the median worker’s reservation wage with respect to the ambient labour share. However, the sign of the derivative of the surrounding PR with respect to the business cycle may be positive or negative, depending on whether DWE or AWE prevails in the neighbouring provinces. Despite this ambiguity, it is possible to carry out a direct test of the BWE, since the second derivative of expression (5) has a clear, well-defined, and unambiguous positive sign.

$$\frac{\partial^2 PR}{\partial Z \partial \left(\frac{\partial PR^N}{\partial Z} \right)} = \frac{\partial PR}{\partial w_M^R} \times \frac{\partial w_M^R}{\partial PR^N} > 0 \quad (5)$$

In other words, if we measure the cyclical sensitivity of the labour participation in a given region (using econometric techniques) and call it β_i^+ , it should be positively related to the average cyclical sensitivity of neighbouring regions, β_i^N . Thus, formally, the relationship (5) could be represented by the expression (6).

$$\frac{\partial \beta_i^N}{\partial \beta_i^+} > 0 \quad (6)$$

The authors suggest that the graphical representation of expression (6) would be the line A-A’ in Figure 4. This graph has a straightforward interpretation, as it would correspond to the Moran scatterplot (with the axis correctly centred around the normalised values of β_i^+ y β_i^N), a tool widely used in spatial analysis.

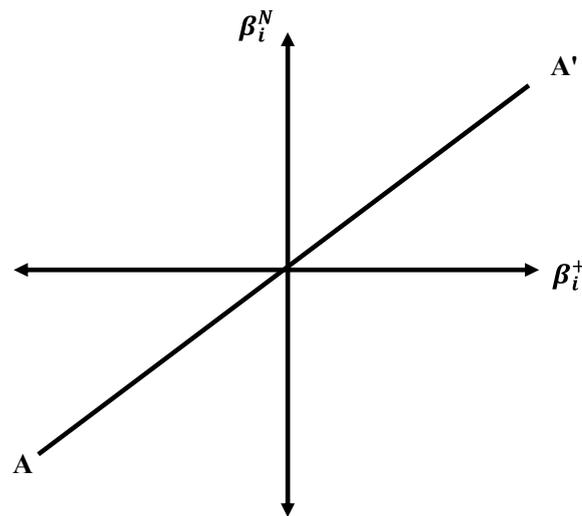


Figure 4. The cyclic sensitivity of the LFPR of an area as a function of the cyclic sensitivity of the LFPR of neighbouring areas.

Otherwise, Figure 4 summarises the conceptual framework and empirical strategy of this research. Consequently, this theoretical framework allows for a straightforward and simple test to validate the BWE, which is fundamental to understanding the cyclical patterns of labour participation in Ecuador's provinces.

Based on this theoretical framework, two hypotheses are put forward and tested using spatial econometric techniques.

Hypothesis 1. *The cyclical sensitivity of labour supply in Ecuadorian provinces shows a positive and significant spatial dependence, confirming a BWE.*

Hypothesis 2. *As the number of nearest neighbours included in the analysis increases, the strength of this relationship decreases.*

4.2. Methodology

To validate the BWE hypothesis in the Ecuadorian region, two steps are carried out. The first consists of estimating the cyclical sensitivity of the participation rate for each of the 23 provinces during the analysis period. To do this, Equation (7) is estimated:

$$\text{LFPRC}_{it} = \alpha_i + \beta_i \text{URC}_{it} + \varepsilon_{it} \quad (7)$$

where LFPRC_{it} corresponds to the LFPR cycle of province i in period t . In turn, URC_{it} contains the UR cycle of province i in period t . The coefficient α_i measures the monthly average level of the cyclical residual of the LFPR in province i that is not explained by fluctuations in the UR cycle. The parameter β_i will measure the cyclical sensitivity of the labour supply in province i . This represents the change in the female LFPRC of province i when the change in URC increases by 1%. If β_i is statistically significant and greater than 0, AWE predominates in the reference province. However, if β_i is less than 0 and statistically significant, DWE predominates. Finally, if β_i is non-significant, then no prior effect dominates over the other. Finally, ε_{it} is a random variable containing the estimation error of the equation for province i in period t .

After estimating the 23 cyclical coefficients of the provincial LFPR, the second methodological step is carried out. This consists of applying a spatial dependence analysis to confirm the existence of the BWE. A neighbourhood criterion will be defined using spatial

weighting matrices to detect the overall spatial dependence and calculate Moran's I, defined by Moran (1948) as follows:

$$I = \frac{n}{S_0} * \frac{\sum_{i,j}^n SW_{i,j} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (8)$$

where n is the sample size, or, in this case, the number of estimated cyclical sensitivities. $SW_{i,j}$ will contain the components of the spatial weight matrix, with X_i representing the value of X in province i , and X_j the value of X in province j . S_0 will be equal to $\sum_i \sum_j SW_{i,j}$ while \bar{X} corresponds to the sample mean of the variable X . Values of I greater than 0 will indicate a positive spatial dependence, while those less than 0 will indicate a negative one. In the case of a Moran's I , values close to 0 will indicate the absence of spatial autocorrelation, suggesting a random distribution of values in space. These results will allow for the validation of the BWE and the linkage of the AWE and DWE to support this hypothesis, showing that labour supply and unemployment are influenced by regional and spatial economic factors.

5. Results

5.1. Baseline Estimates

Table 3 shows the cyclical sensitivity of the LFPR in the 23 provinces of Ecuador over the period 2021:m1–2024:m4, using a Hodrick-Prescott (HP) filter with a smoothing parameter $\lambda = 14,400$. The coefficients β (beta) indicate the relationship between the LFPR cycle and the business cycle, the latter captured by movements in the UR cycle, with their respective p -values, t -statistics and R-squared (R^2).

Table 3. Cyclical sensitivity of the LFPR (2021:m1–2024:m4) (HP $\lambda = 14,400$).

Province	β	p -Value	t -Statistic	R^2
Azuay	−0.552	0.243	−1.190	0.036
Bolivar	−0.770	0.318	−1.010	0.026
Cañar	−0.636	0.255	−1.150	0.034
Carchi	−0.151	0.689	−0.400	0.004
Chimborazo	−0.763 ***	0.026	−2.310	0.123
Cotopaxi	−1.044 ***	0.043	−2.090	0.103
El Oro	−0.161	0.472	−0.730	0.014
Esmeraldas	0.058	0.774	0.290	0.002
Guayas	0.367	0.255	1.150	0.034
Imbabura	−0.359	0.218	−1.250	0.040
Loja	−0.167	0.765	−0.300	0.002
Los Rios	0.097	0.807	0.250	0.002
Manabí	0.330	0.490	0.700	0.013
Morona Santiago	−1.443 *	0.089	−1.740	0.074
Napo	−2.354 ***	0.001	−3.740	0.270
Orellana	−1.003 ***	0.002	−3.340	0.227
Pastaza	−2.812 ***	0.000	−5.900	0.479
Pichincha	−0.362	0.125	−1.570	0.061
Santa Elena	−0.015	0.968	−0.040	0.000
Santo Domingo	−0.189	0.648	−0.460	0.006
Sucumbíos	−1.283 ***	0.006	−2.940	0.185
Tungurahua	−0.328	0.418	−0.820	0.017
Zamora Chinchipe	−0.906	0.113	−1.620	0.065

Notes: * and *** indicate the statistical significance of the parameter at the 10%, and 1% levels, respectively.

Most provinces have negative coefficients, suggesting that participation falls in response to an adverse economic cycle. Seven statistically significant coefficients are observed over the period analysed. DWE dominates AWE in Chimborazo, Cotopaxi, Morona

Santiago, Orellana, and Sucumbíos. It is particularly strong in provinces such as Napo and Pastaza.

We then use spatial econometric techniques to examine whether there is a social influence on the cyclical patterns of labour participation using the 23 estimated coefficients. The theoretical model suggests that the cyclical behaviour of a region is positively related to that of its neighbours, which is known as the BWE. To test this, spatial nearest neighbour weight matrices (K_{nn} ; where K represents the number of nearest neighbours considered for each region, with K ranging from 1 to 10) are used to continuously measure spatial proximity and to assess the importance of proximity in the observed social effects. Specifically, K indicates how many of the nearest neighbouring regions are included in determining the spatial influence on each given region. For example, when $K = 1$, only the nearest neighbour is considered, whereas when $K = 10$, the ten nearest neighbours are included. The weight matrices have the following specification of spatial weights (W):

$$W_{ij} \begin{cases} 1, & \text{if the centroid of } j \text{ is one of the } k \text{ centroids nearest to that of } i. \\ 0, & \text{otherwise} \end{cases}$$

Table 4 and Figure 5 show the results of the spatial dependence analysis for the cyclical patterns in the 23 provinces of the Ecuadorian economy, using the overall Moran index (I) and the corresponding p -value for different numbers of nearest neighbours (K_{nn}). A strong and significant spatial dependence in the cyclical patterns of the Ecuadorian economy is observed when three or more nearest neighbours ($K_{nn} \geq 3$) are considered.

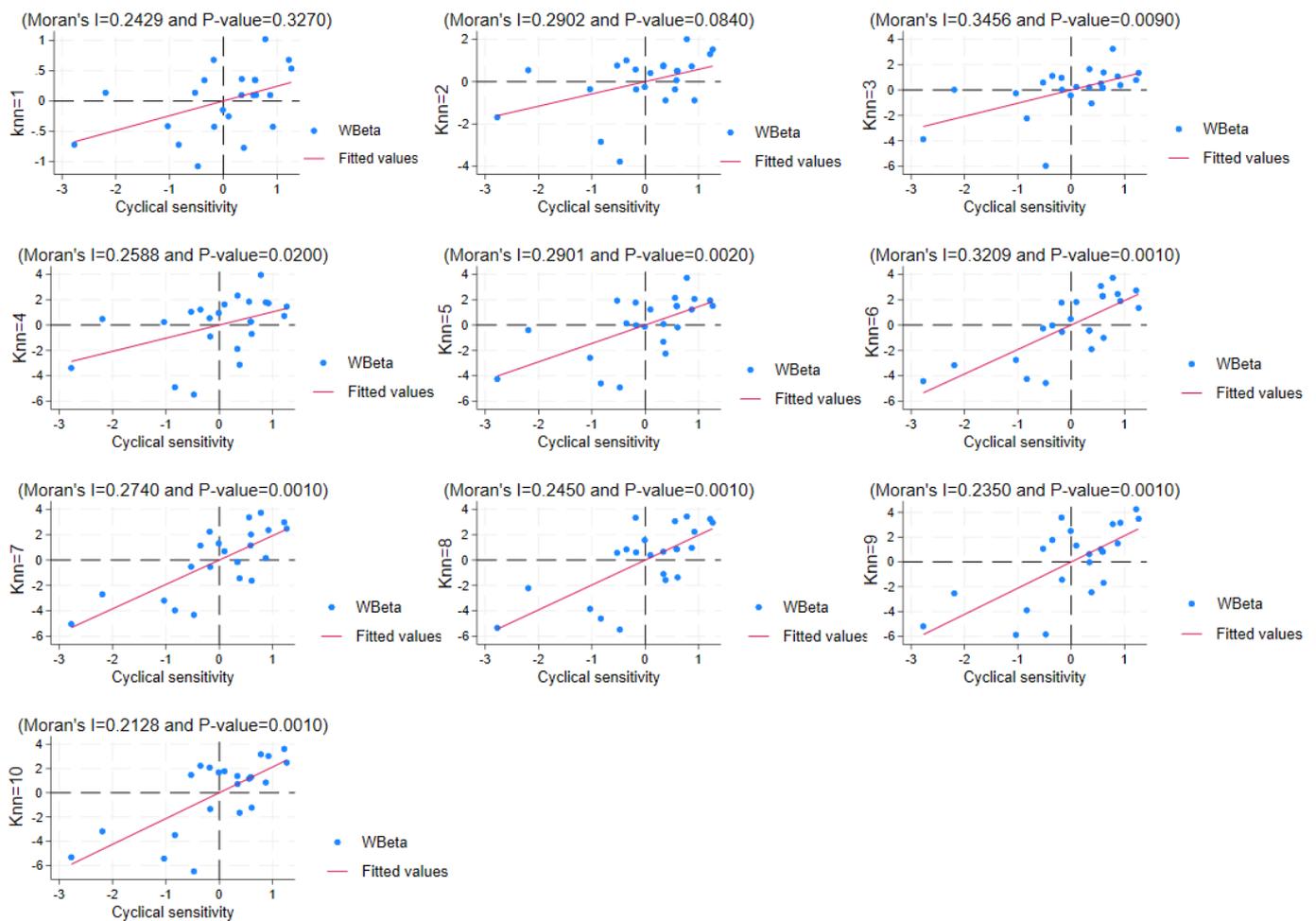


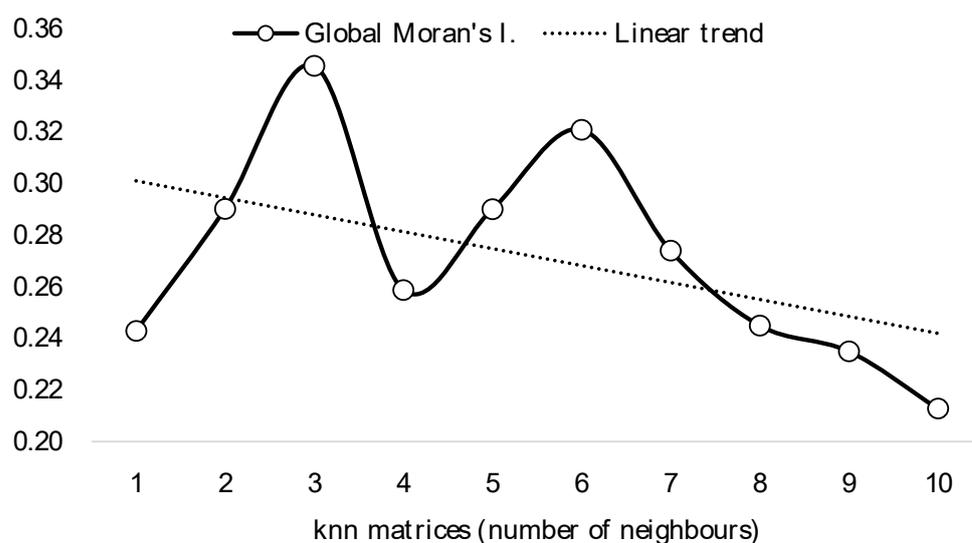
Figure 5. Overall scatter plots of Moran’s I (2021:m1–2024:m4) (HP $\lambda = 14,400$).

Table 4. Spatial dependency analysis (2021:m1–2024:m4) (HP $\lambda = 14,400$).

	Global Moran's I.	E(I)	Std Dev.	Z-Score	p-Value
Knn = 1	0.2429	−0.0455	0.2546	1.1326	0.327
Knn = 2	0.2902	−0.0455	0.1770	1.8967	0.084
Knn = 3	0.3456	−0.0455	0.1374	2.8467	0.009
Knn = 4	0.2588	−0.0455	0.1165	2.6109	0.02
Knn = 5	0.2901	−0.0455	0.1037	3.2345	0.002
Knn = 6	0.3209	−0.0455	0.0921	3.9788	0.001
Knn = 7	0.274	−0.0455	0.0810	3.9443	0.001
Knn = 8	0.245	−0.0455	0.0719	4.0393	0.001
Knn = 9	0.235	−0.0455	0.0647	4.3326	0.001
Knn = 10	0.2128	−0.0455	0.0575	4.4927	0.001

In the spatial econometric modelling process, all beta coefficients, both significant and insignificant, were initially included to ensure the completeness of the analysis and to allow a robust assessment of all possible effects. Subsequently, it was found that assigning a value of zero to non-significant coefficients did not change the results of the model⁵. The relationships in favour of BWE continued to show significant positive autocorrelation. This validation shows that the robustness of the model does not depend on the value of the non-significant coefficients and that the key spatial relationships remain stable. This approach ensures the interpretation of the model without compromising the validity and significance of the observed spatial relationships. The results presented in Figure 5 are therefore confirmed.

One of the aims of this research was to determine whether the intensity of the social effect varies according to spatial proximity. The results shown in Figure 6 may help to confirm this hypothesis. It shows that the strength of the effect decreases as the number of neighbours considered increases, although it remains significant up to Knn = 10. This implies that nearest regions have a stronger influence on business cycle patterns, while the influence of more distant regions is less strong. Therefore, economic policies in Ecuador should take into account these spatial effects and focus first on the nearest regions in order to be more effective.

**Figure 6.** Evolution of global spatial dependence (2021:m1–2024:m4) (HP $\lambda = 14,400$).

5.2. Robustness Analysis

5.2.1. Filtering of the Series

To calculate the cyclical sensitivities of labour supply, we adjusted the parameter $\lambda = 1600$ proposed by Hodrick and Prescott (1997) for quarterly data, multiplying it by the

square of the frequency of observations relative to quarterly data (three months per quarter). This yielded a parameter of $\lambda = 14,400$, following [Backus and Kehoe \(1992\)](#). However, we decided to assess the robustness of our results by applying the approach proposed by [Ravn and Uhlig \(2002\)](#), who suggest adjusting the value of $\lambda = 1600$ by raising the frequency to the fourth power, which results in a value of $\lambda = 129,600$.

The evolution of the series using this new methodology is presented in Appendix B of this research (Figures A2 and A3). In this Appendix, the calculation of cyclical sensitivities for each province is included (Table A2), as well as the analysis of the corresponding spatial dependence (Table A3, Figures A4 and A5; Table A4 and Figure A6).

We can confirm that the results did not change with respect to the case of $\lambda = 14,400$. With a value of $\lambda = 129,600$, we continued to observe a predominance of the DWE over the AWE in eight provinces of the country, notably highlighting (although at a 10% significance level) the province of Pichincha, one of the largest in Ecuador. Factors such as spatial dependence remained relevant, especially for three or more nearest neighbours ($K_{nn} \geq 3$). The presence of the BWE was confirmed at the regional level, even validating this effect by assigning a value of zero to the non-significant coefficients of the cyclical sensitivity. Additionally, it was observed that, as the number of nearest neighbours increased, the relationship with the BWE weakened.

Therefore, under these scenarios, we reaffirm that the relationships found for $\lambda = 14,400$ are robust when considering other approaches, as demonstrated here with $\lambda = 129,600$.

5.2.2. Use of Alternative Spatial Weighting Matrices

In this study, we used spatial weighting matrices based on the K nearest neighbours method (where K varies from 1 to 10) to delve deeper into the spatial dependence of the cyclical sensitivity of labour supply in the 23 provinces of Ecuador. This approach allowed us to capture how immediate spatial interactions affect regional labour dynamics in the country.

To complement our analysis and ensure the robustness of the results, we incorporated alternative spatial weighting matrices known as contiguity matrices. These matrices consider as neighbours only those provinces that share a boundary, either through common edges or vertices. By including this approach, we aimed to determine whether the spatial relationships identified are sensitive to the specification of the weighting matrix used.

While nearest neighbours matrices define neighbourhoods based on geographic proximity and connect each unit to its K nearest neighbours regardless of whether they share borders, contiguity matrices focus on direct geographic adjacency. This allows us to capture spatial influences that specifically occur between contiguous provinces, thereby complementing the analysis conducted with the nearest neighbours approach.

When applying the spatial dependence analysis with the contiguity matrix, Table 5 confirms a positive and significant global Moran's index. The scatter plot in Figure 7 reaffirms the positive spatial dependence previously identified with the nearest neighbours matrices. This finding suggests that our results are robust to different specifications of the spatial weighting matrix, which strengthens the validity of our conclusions.

Table 5. Spatial dependency analysis (2021:m1–2024:m4) (HP $\lambda = 14,400$).

Spatial Weight Matrix	Global Moran's I.	E(I)	Std Dev.	Z-Score	p-Value
Queen contiguity	0.425	−0.045	0.118	3.967	0.000

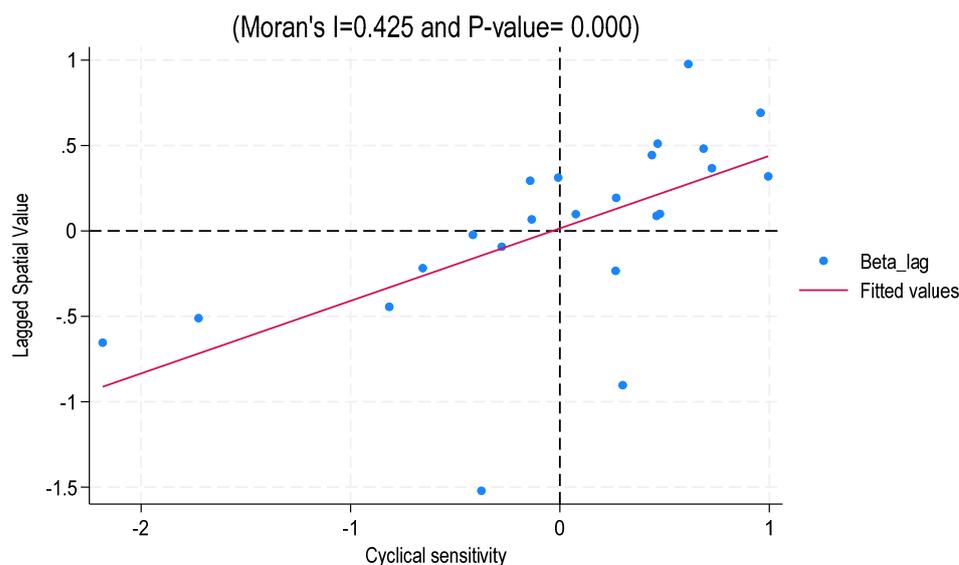


Figure 7. Evolution of global spatial dependence by contiguity (2021:m1–2024:m4) (HP $\lambda = 14,400$).

5.2.3. Local Spatial Dependence Analysis

So far, our analysis has focused on global spatial dependence using Moran's index (1948). However, to delve deeper into the local dynamics that might be hidden in this approach, we introduce the Local Indicators of Spatial Association (LISA) proposed by Anselin (1995). LISA allows us to decompose the global Moran's index and quantify significant spatial clustering according to the type of autocorrelation. This facilitates examining the specific contribution of each province to the overall spatial autocorrelation, capturing both the degree of spatial association and the heterogeneity derived from the individual contribution of each spatial unit.

Peluso et al. (2024) establish that LISA statistics serve two essential purposes: first, they act as indicators of local hotspots, allowing for the identification of specific clusters within the geographical space; second, they facilitate the assessment of the influence of individual locations on the magnitude of the global statistic. This dual functionality provides us with a valuable tool to understand in greater detail the spatial structure of the data and the local dynamics present.

Appendix B includes the results of the local dependence analysis for the 23 provinces of the country, considering from the first nearest neighbour to the tenth. Table A5 presents the local Moran's index, its expected value, and other statistics of interest. In all cases where the local Moran's index was significant, positive spatial dependence was observed. For a better visual understanding of these results, Figure 8 provides a georeferencing of the significant LISA indicators for each province (starting from the second nearest neighbour, since at this level, spatial relationships become significant).

The figure shows how spatial relationships vary depending on the number of nearest neighbours (k). The provinces that mainly contribute locally to the overall spatial dependence are Guayas in the Coastal region and Pastaza in the Amazon region. As the neighbourhood concept is expanded, provinces such as Manabí, Los Ríos, and Santa Elena in the Coastal region, as well as Orellana, Sucumbíos, Morona Santiago, and Napo in the Amazon region, are included.

The maps reaffirm the positive spatial autocorrelation evidenced by the global Moran's index calculated in previous sections, as spatial dependence patterns in the form of "High-High" and "Low-Low" clusters are observed. These clusters indicate a direct relationship between areas with high and low influence on labour participation in their neighbouring regions, thus evidencing a spatial concentration of similar patterns.

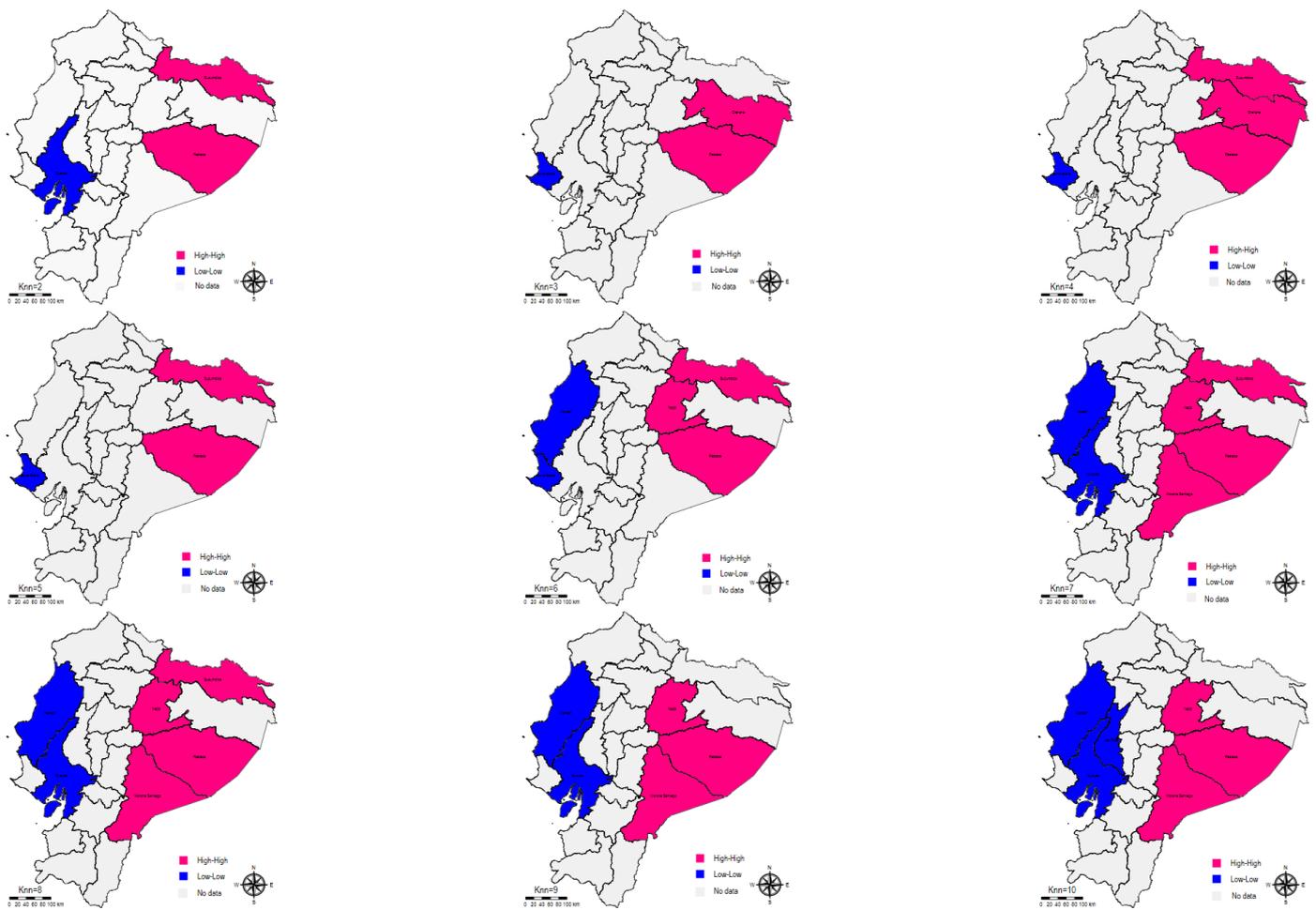


Figure 8. LISA cluster map for cyclical sensitivity of labour supply.

In the case of the provinces in the Amazon region classified within a “High-High” cluster, it is observed that the DWE, characterised by high cyclical sensitivity of labour supply (see Table 3), extends to neighbouring provinces, generating a consistent spatial pattern. That is, these provinces not only exhibit a strong response to economic cycle fluctuations, but they also reflect regional contagion of the discouraged effect, contributing to the formation of a homogeneous cluster with a high impact on labour participation.

On the other hand, in the provinces of the Coastal region, characterised by a general tendency towards the AWE in their cyclical sensitivity (although not significant; see Table 3), the classification within a “Low-Low” cluster suggests that, although the impact of AWE is slight, this pattern tends to replicate among neighbouring provinces. This indicates a spatial dynamic in which, although the magnitude of the effect is not pronounced, there is a certain regional coherence that favours the propagation of this response, thus contributing to the formation of a low-intensity cluster in positive labour participation.

This analysis strengthens the results found at the global level, as we have identified similar patterns at the local level with clear spillover effects. By appreciating which provinces mainly contribute to the overall spatial dependence, we not only strengthen the findings of the research but also obtain relevant information to consider in the application of economic policy strategies aimed at improving the regional labour market in Ecuador.

6. Conclusions and Policy Recommendations

This study examined the spatial dependence in the cyclical sensitivity of labour supply in 23 provinces of Ecuador for the period 2021–2024, using spatial econometric techniques. The results confirm the existence of a positive and significant spatial dependence in the

cyclical sensitivity of labour supply, thus confirming the BWE in the Ecuadorian context. Against this background, Hypothesis 1 of the study is confirmed. That is, labour decisions in one province are influenced by decisions in neighbouring provinces, highlighting the regional interdependence in the Ecuadorian labour market.

Most provinces have negative coefficients for the cyclical sensitivity of labour force participation, indicating that labour supply decreases in response to an adverse economic cycle. DWE dominates AWE in provinces such as Chimborazo, Cotopaxi, Morona Santiago, Orellana, and Sucumbíos. A strong and significant spatial dependence in the cyclical patterns of labour participation was observed when considering three or more nearest neighbours ($K_{nn} \geq 3$). At the same time, this finding allowed us to validate Hypothesis 2 of this study, as it was found that nearest regions have a greater influence on cyclical patterns, while the influence of more distant regions is less significant.

The analysis using LISA allowed us to decompose the global Moran's index, thus facilitating the evaluation of the specific contribution of each province to the overall spatial autocorrelation. The formation of "High-High" and "Low-Low" spatial clusters was evidenced, highlighting the existence of local dependence patterns that underscore the importance of understanding both global and local dynamics when designing labour policies. In particular, the provinces in the Amazon region contributed significantly to the overall spatial dependence through a strong DWE, which resulted in a greater withdrawal from the labour market during recession periods, not only in these provinces but also in their immediate neighbours. In contrast, in provinces in the Coastal region, such as Guayas, although the AWE is relatively weak, it could reflect the existence of barriers to entry into the labour market.

The results suggest that economic policies should take spatial interdependencies into account when designing labour market interventions. Policies that ignore these interdependencies may be less effective and may not adequately address regional dynamics. It is therefore recommended to implement regional development policies that take account of spatial interdependencies. This could include employment and training programmes that are designed to be implemented simultaneously in neighbouring provinces to maximise their effectiveness. In addition, transport and communication infrastructure between provinces should be improved to facilitate labour and economic mobility and reduce barriers that limit economic and labour interactions between regions.

Establishing employment support programmes tailored to the specific needs of each region, taking into account both local economic factors and spatial influences from neighbouring provinces, could be an effective strategy. It is equally important to establish monitoring and evaluation systems that use spatial data to track the effectiveness of employment policies and make adjustments based on feedback from neighbouring provinces.

This study provides a deeper understanding of the spatial dynamics of the labour market in Ecuador, highlighting the importance of regional interdependencies. The validation of the BWE in Ecuadorian provinces underlines the need to design public policies that take these interdependencies into account in order to improve the effectiveness of labour market interventions. The results of this research not only contribute to the economic literature, but also provide a solid basis for the development of more equitable and efficient economic policies in Ecuador.

However, despite these significant findings and the verification of their robustness, this study presents certain limitations. For future research, it would be advisable to extend the period of analysis or work with annual data for better representativeness of the information, which would allow for greater generalisation of the results to different temporal contexts and provide deeper insights into their stability. Furthermore, incorporating additional socioeconomic and demographic variables to the spatial weighting matrices modelling, as well as exploring alternative methodologies, would facilitate a deeper understanding of regional interdependencies and their impact on the cyclical sensitivity of labour supply in Ecuador. These approaches could enhance the precision of the analyses and provide a more comprehensive view of the dynamics of the regional labour market.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

In this Appendix, Table A1 and Figure A1 show the results of the spatial dependence analysis of the cyclical patterns in the 23 provinces of the Ecuadorian economy, replacing the value of zero in the coefficients that were not significant in Table 3 of this research.

Table A1. Spatial dependency analysis (2021:m1–2024:m4) (HP $\lambda = 14,400$).

	Global Moran's I.	E(I)	Std Dev.	Z-Score	p-Value
Knn = 1	0.2773	−0.0455	0.2546	1.2680	0.249
Knn = 2	0.3115	−0.0455	0.1770	2.0169	0.061
Knn = 3	0.3663	−0.0455	0.1374	2.9978	0.006
Knn = 4	0.2572	−0.0455	0.1165	2.5974	0.016
Knn = 5	0.2765	−0.0455	0.1037	3.1038	0.002
Knn = 6	0.3047	−0.0455	0.0921	3.8022	0.001
Knn = 7	0.2574	−0.0455	0.0810	3.7397	0.001
Knn = 8	0.2309	−0.0455	0.0719	3.8431	0.001
Knn = 9	0.2257	−0.0455	0.0647	4.1886	0.001
Knn = 10	0.1957	−0.0455	0.0575	4.1952	0.001

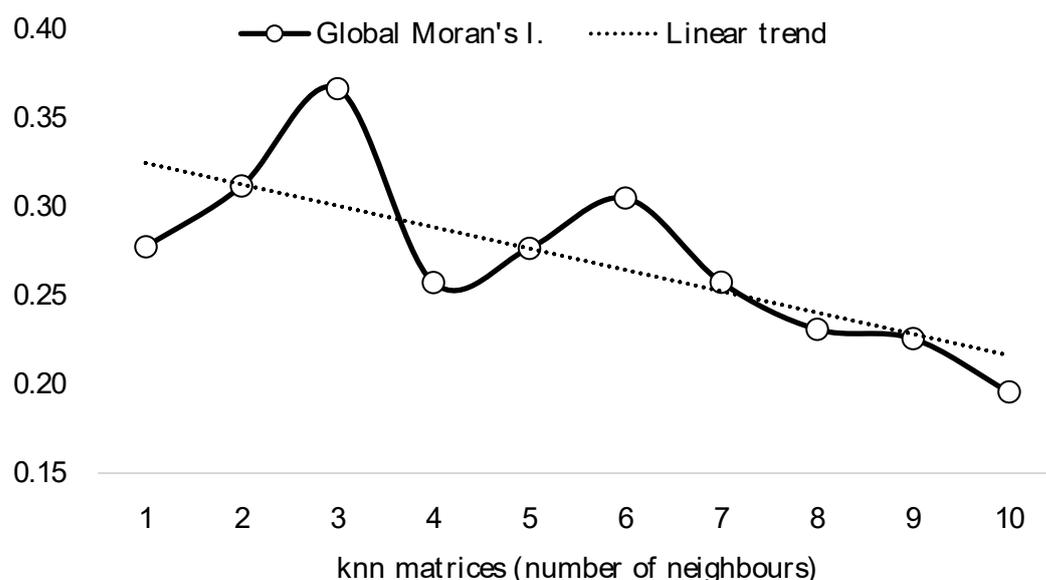


Figure A1. Evolution of global spatial dependence (2021:m1–2024:m4) (HP $\lambda = 14,400$).

Appendix B

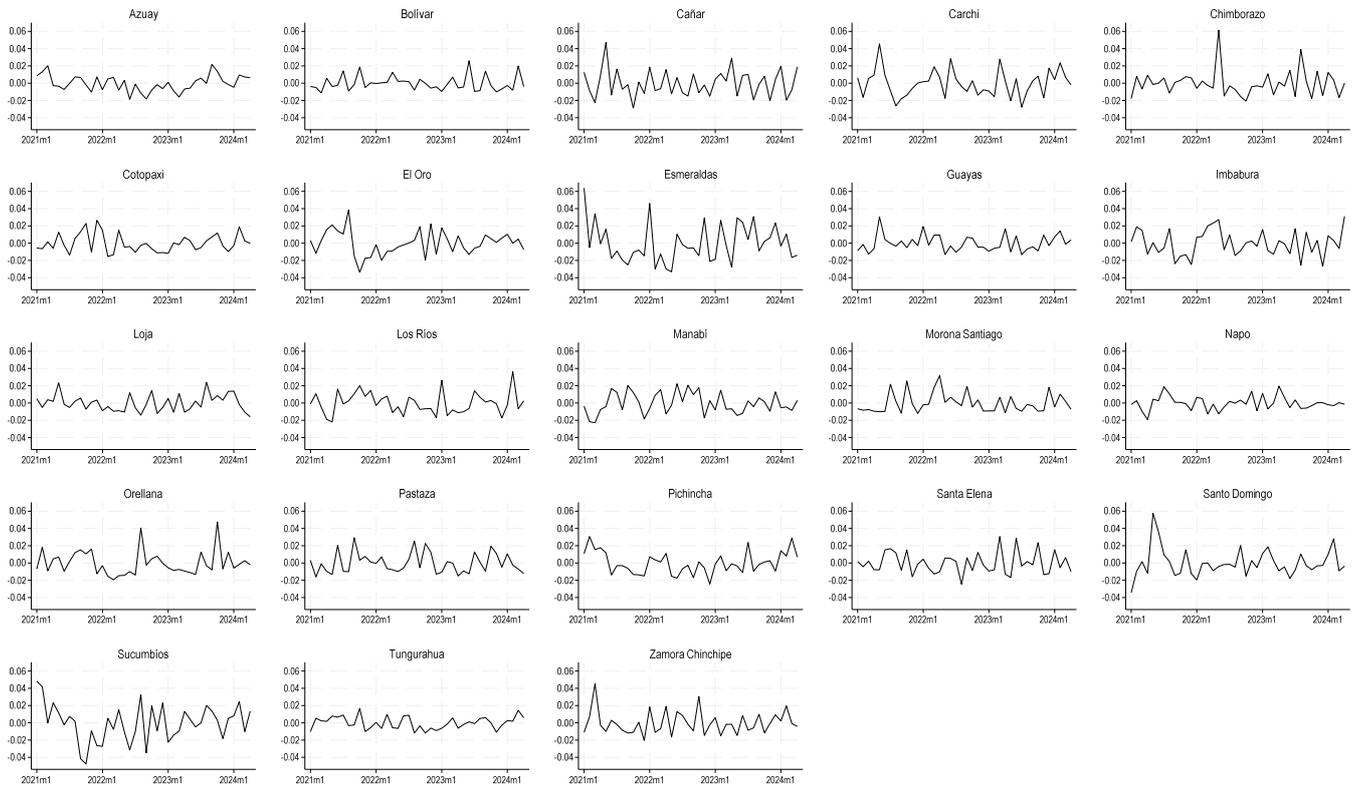


Figure A2. Cycle of the unemployment rate by province (HP $\lambda = 129,600$). Source: ENEMDU–INEC. Own elaboration.

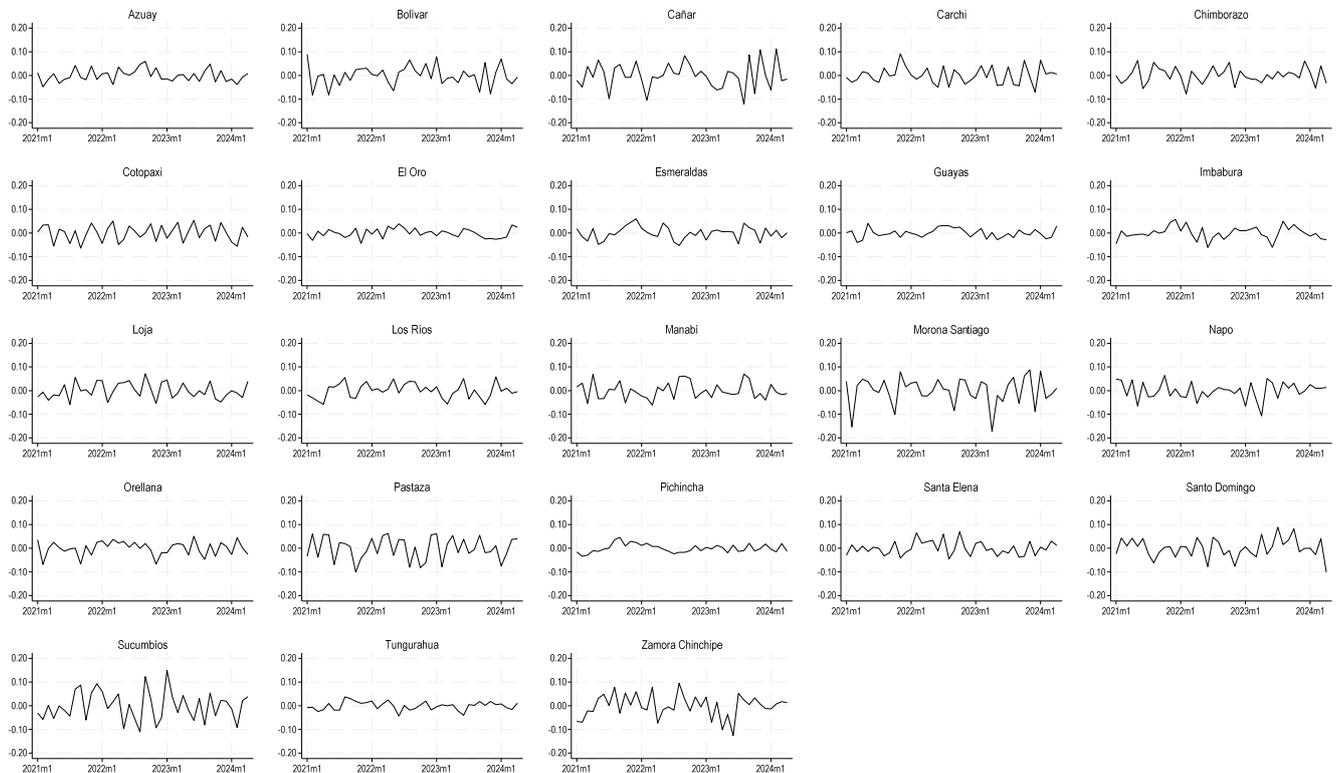


Figure A3. Cycle of the labour force participation rate by province (HP $\lambda = 129,600$). Source: ENEMDU–INEC. Own elaboration.

Table A2. Cyclical sensitivity of the LFPR (2021:m1–2024:m4) (HP $\lambda = 129,600$).

Province	β	<i>p</i> -Value	t-Statistic	R ²
Azuay	−0.686	0.127	−1.560	0.060
Bolivar	−0.742	0.338	−0.970	0.024
Cañar	−0.637	0.254	−1.160	0.034
Carchi	−0.144	0.701	−0.390	0.004
Chimborazo	−0.760 **	0.027	−2.300	0.122
Cotopaxi	−1.054 **	0.040	−2.130	0.083
El Oro	−0.185	0.411	−0.830	0.018
Esmeraldas	0.038	0.846	0.200	0.001
Guayas	0.352	0.278	1.100	0.031
Imbabura	−0.369	0.208	−1.280	0.041
Loja	−0.257	0.647	−0.460	0.006
Los Rios	0.082	0.840	0.200	0.001
Manabí	0.327	0.487	0.700	0.013
Morona Santiago	−1.389 *	0.098	−1.700	0.071
Napo	−2.392 ***	0.001	−3.760	0.271
Orellana	−1.007 ***	0.002	−3.370	0.230
Pastaza	−2.804 ***	-	−5.910	0.479
Pichincha	−0.372 *	0.094	−1.720	0.072
Santa Elena	−0.031	0.935	−0.080	0.000
Santo Domingo	−0.188	0.650	−0.460	0.006
Sucumbíos	−1.256 ***	0.005	−2.990	0.190
Tungurahua	−0.305	0.444	−0.770	0.016
Zamora Chinchipe	−0.917	0.110	−1.640	0.066

Notes: *, **, and *** indicate the statistical significance of the parameter at the 10%, 5%, and 1% levels, respectively.

Table A3. Spatial dependency analysis (2021:m1–2024:m4) (HP $\lambda = 129,600$).

	Global Moran's I.	E(I)	Std Dev.	Z-Score	<i>p</i> -Value
Knn = 1	0.2330	−0.0455	0.2546	1.0941	0.339
Knn = 2	0.2758	−0.0455	0.177	1.8153	0.099
Knn = 3	0.3425	−0.0455	0.1374	2.8243	0.009
Knn = 4	0.2492	−0.0455	0.1165	2.529	0.025
Knn = 5	0.2783	−0.0455	0.1037	3.1216	0.005
Knn = 6	0.3112	−0.0455	0.0921	3.8732	0.001
Knn = 7	0.2672	−0.0455	0.081	3.8602	0.001
Knn = 8	0.2390	−0.0455	0.0719	3.9556	0.001
Knn = 9	0.2289	−0.0455	0.0647	4.2388	0.001
Knn = 10	0.2064	−0.0455	0.0575	4.3817	0.001

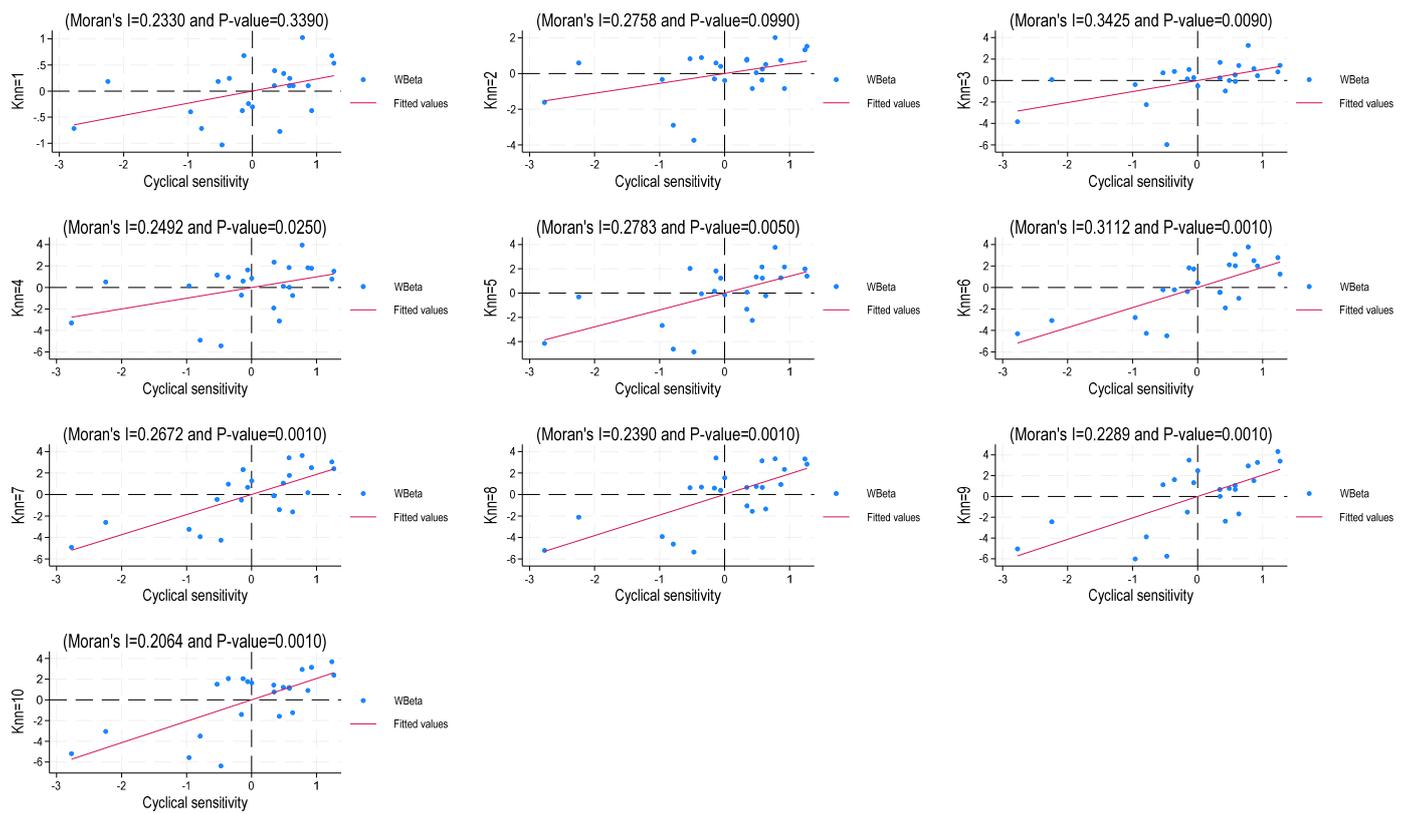


Figure A4. Overall scatter plots of Moran's I. Notes: Data 2021:m1–2024:m4, HP $\lambda = 129,600$.

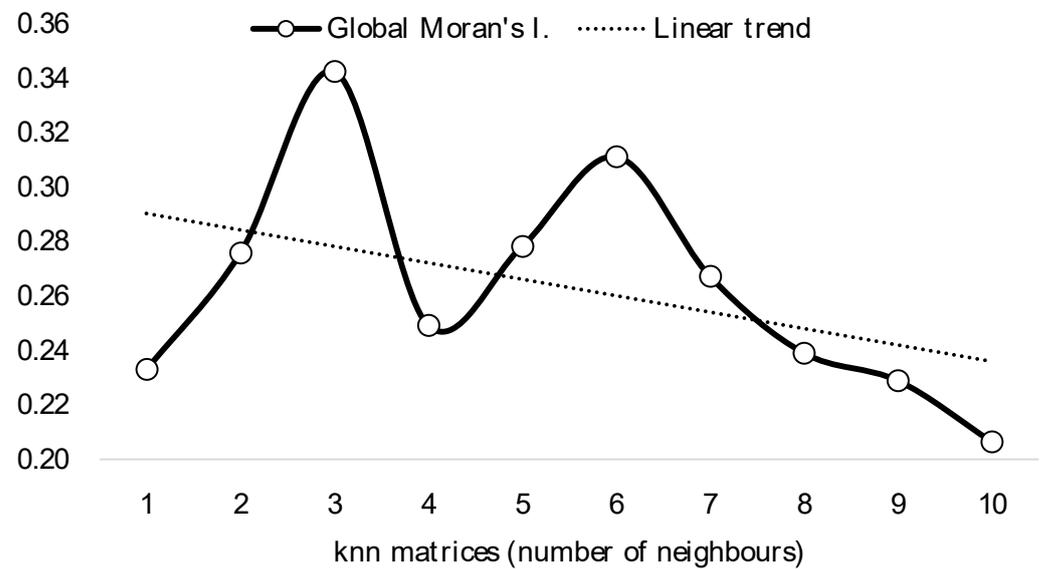


Figure A5. Evolution of global spatial dependence (2021:m1–2024:m4) (HP $\lambda = 129,600$).

Table A4. Spatial dependency analysis with non-significant β replaced by zero (2021:m1–2024:m4) (HP $\lambda = 129,600$).

	Global Moran's I.	E(I)	Std Dev.	Z-Score	p -Value
Knn = 1	0.2592	−0.0455	0.2546	1.1967	0.291
Knn = 2	0.3064	−0.0455	0.177	1.9882	0.068
Knn = 3	0.3707	−0.0455	0.1374	3.0299	0.005
Knn = 4	0.2733	−0.0455	0.1165	2.7351	0.008
Knn = 5	0.2853	−0.0455	0.1037	3.1889	0.001
Knn = 6	0.3164	−0.0455	0.0921	3.9294	0.001
Knn = 7	0.2649	−0.0455	0.081	3.8322	0.001
Knn = 8	0.2361	−0.0455	0.0719	3.9164	0.001
Knn = 9	0.2291	−0.0455	0.0647	4.2412	0.001
Knn = 10	0.2031	−0.0455	0.0575	4.3239	0.001

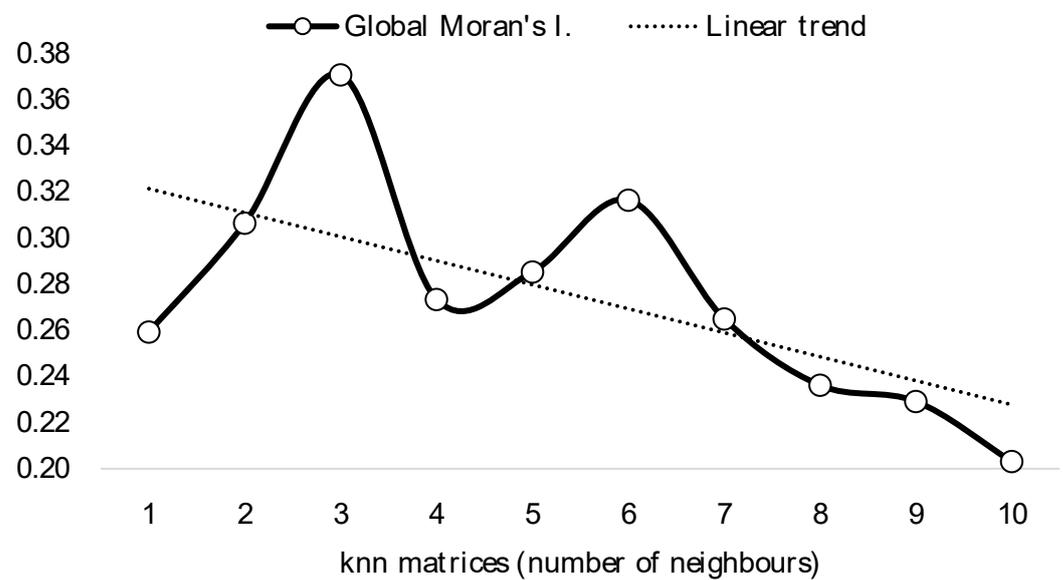
**Figure A6.** Evolution of global spatial dependence with non-significant β replaced by zero (2021:m1–2024:m4) (HP $\lambda = 129,600$).

Table A5. Local Indicators of Spatial Association (LISA).

Province	Knn = 1				Knn = 2				Knn = 3				Knn = 4				Knn = 5			
	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z
Napo	-0.87	-0.05	0.92	-0.90	-1.65	-0.09	1.28	-1.22	-0.44	-0.14	1.53	-0.20	-1.22	-0.18	1.73	-0.60	0.69	-0.23	1.89	0.48
Zamora Chinchipe	-0.22	-0.05	0.92	-0.19	-0.44	-0.09	1.28	-0.27	-0.47	-0.14	1.53	-0.22	-0.47	-0.18	1.73	-0.17	-0.09	-0.23	1.89	0.08
Tungurahua	-0.21	-0.05	0.92	-0.18	-0.28	-0.09	1.28	-0.15	-0.35	-0.14	1.53	-0.14	-1.22	-0.18	1.73	-0.60	-0.86	-0.23	1.89	-0.33
Cotopaxi	-0.21	-0.05	0.92	-0.18	-0.52	-0.09	1.28	-0.34	-0.42	-0.14	1.53	-0.18	-0.6	-0.18	1.73	-0.24	-1.11	-0.23	1.89	-0.47
Los Ríos	-0.17	-0.05	0.92	-0.14	-0.68	-0.09	1.28	-0.46	0.54	-0.14	1.53	0.44	1.71	-0.18	1.73	1.09	2.07	-0.23	1.89	1.22
Bolívar	-0.17	-0.05	0.92	-0.14	-0.14	-0.09	1.28	-0.04	-0.21	-0.14	1.53	-0.05	-0.11	-0.18	1.73	0.04	-0.35	-0.23	1.89	-0.07
Azuay	0	-0.05	0.92	0.05	0.06	-0.09	1.28	0.12	0.04	-0.14	1.53	0.12	0.17	-0.18	1.73	0.20	0.13	-0.23	1.89	0.19
Cañar	0	-0.05	0.92	0.05	0	-0.09	1.28	0.07	0	-0.14	1.53	0.09	-0.01	-0.18	1.73	0.10	0	-0.23	1.89	0.12
Chimborazo	0.03	-0.05	0.92	0.09	0.03	-0.09	1.28	0.10	-0.03	-0.14	1.53	0.07	0.15	-0.18	1.73	0.19	-0.01	-0.23	1.89	0.11
Pichincha	0.12	-0.05	0.92	0.18	0.32	-0.09	1.28	0.32	0.13	-0.14	1.53	0.18	-0.64	-0.18	1.73	-0.27	-0.43	-0.23	1.89	-0.11
Morona Santiago	0.19	-0.05	0.92	0.25	0.2	-0.09	1.28	0.23	0.09	-0.14	1.53	0.15	-0.32	-0.18	1.73	-0.08	2.68 *	-0.23	1.89	1.54
Santo Domingo	0.2	-0.05	0.92	0.26	-0.11	-0.09	1.28	-0.02	0.4	-0.14	1.53	0.35	1.11	-0.18	1.73	0.75	1.31	-0.23	1.89	0.81
Imbabura	0.22	-0.05	0.92	0.28	0.34	-0.09	1.28	0.34	0.65	-0.14	1.53	0.51	0.85	-0.18	1.73	0.60	0.07	-0.23	1.89	0.15
Carchi	0.22	-0.05	0.92	0.28	0.43	-0.09	1.28	0.41	0.98	-0.14	1.53	0.73	-0.41	-0.18	1.73	-0.13	-0.05	-0.23	1.89	0.09
Esmeraldas	0.31	-0.05	0.92	0.39	0.82	-0.09	1.28	0.71	1.13	-0.14	1.53	0.83	1.68	-0.18	1.73	1.08	1.2	-0.23	1.89	0.75
El Oro	0.36	-0.05	0.92	0.44	0.42	-0.09	1.28	0.40	0.2	-0.14	1.53	0.22	0.2	-0.18	1.73	0.22	0.98	-0.23	1.89	0.64
Loja	0.36	-0.05	0.92	0.44	0.15	-0.09	1.28	0.19	0.21	-0.14	1.53	0.22	0.2	-0.18	1.73	0.22	0.97	-0.23	1.89	0.64
Sucumbíos	0.41	-0.05	0.92	0.50	2.32 **	-0.09	1.28	1.89	1.79	-0.14	1.53	1.26	4.2 ***	-0.18	1.73	2.54	3.91 **	-0.23	1.89	2.19
Orellana	0.41	-0.05	0.92	0.50	1.8 *	-0.09	1.28	1.48	2.89 **	-0.14	1.53	1.98	2.7 **	-0.18	1.73	1.67	2.4 *	-0.23	1.89	1.39
Guayas	1.03	-0.05	0.92	1.17	2.25 **	-0.09	1.28	1.83	2.01 *	-0.14	1.53	1.40	1.99	-0.18	1.73	1.26	2.12	-0.23	1.89	1.24
Santa Elena	1.03	-0.05	0.92	1.17	1.78 *	-0.09	1.28	1.47	2.77 **	-0.14	1.53	1.90	3.25 **	-0.18	1.73	1.99	3.11 **	-0.23	1.89	1.76
Manabí	1.17 *	-0.05	0.92	1.32	1.88 *	-0.09	1.28	1.55	1.21	-0.14	1.53	0.88	0.98	-0.18	1.73	0.67	2.59 *	-0.23	1.89	1.49
Pastaza	1.38 *	-0.05	0.92	1.55	4.38 ***	-0.09	1.28	3.51	10.74 ***	-0.14	1.53	7.10	9.63 ***	-0.18	1.73	5.68	12.04 ***	-0.23	1.89	6.49

Table A5. Cont.

Province	Knn = 6				Knn = 7				Knn = 8				Knn = 9				Knn = 10			
	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z	Ii	E(Ii)	Sd (Ii)	z
Napo	7.04 ***	-0.27	2.02	3.62	5.76 ***	-0.32	2.13	2.86	4.37 **	-0.36	2.22	2.14	5.47 ***	-0.41	2.29	2.57	5.88 ***	-0.46	2.34	2.70
Zamora Chinchipe	-0.02	-0.27	2.02	0.12	-0.49	-0.32	2.13	-0.08	-0.42	-0.36	2.22	-0.03	-0.71	-0.41	2.29	-0.13	-1.05	-0.46	2.34	-0.25
Tungurahua	-0.72	-0.27	2.02	-0.22	-0.5	-0.32	2.13	-0.09	-0.5	-0.36	2.22	-0.06	-0.92	-0.41	2.29	-0.22	-0.41	-0.46	2.34	0.02
Cotopaxi	0.1	-0.27	2.02	0.18	0.19	-0.32	2.13	0.24	-0.48	-0.36	2.22	-0.05	-0.67	-0.41	2.29	-0.11	-1.15	-0.46	2.34	-0.30
Los Ríos	1.91	-0.27	2.02	1.08	2.45 *	-0.32	2.13	1.30	2.44	-0.36	2.22	1.26	3.19 *	-0.41	2.29	1.57	3.51 **	-0.46	2.34	1.69
Bolívar	-0.35	-0.27	2.02	-0.04	-0.46	-0.32	2.13	-0.07	-0.69	-0.36	2.22	-0.15	-0.7	-0.41	2.29	-0.13	-0.51	-0.46	2.34	-0.02
Azuay	0.19	-0.27	2.02	0.23	0.09	-0.32	2.13	0.19	0.07	-0.36	2.22	0.20	0.15	-0.41	2.29	0.24	0.24	-0.46	2.34	0.30
Cañar	-0.01	-0.27	2.02	0.13	-0.02	-0.32	2.13	0.14	-0.02	-0.36	2.22	0.16	-0.03	-0.41	2.29	0.17	-0.02	-0.46	2.34	0.18
Chimborazo	0.08	-0.27	2.02	0.18	0.06	-0.32	2.13	0.18	-0.16	-0.36	2.22	0.09	0.23	-0.41	2.29	0.28	0.13	-0.46	2.34	0.25
Pichincha	-0.12	-0.27	2.02	0.08	0.01	-0.32	2.13	0.16	0.34	-0.36	2.22	0.32	0.28	-0.41	2.29	0.30	0.71	-0.46	2.34	0.50
Morona Santiago	2.88 *	-0.27	2.02	1.56	3.26 **	-0.32	2.13	1.68	3.83 **	-0.36	2.22	1.89	6.2 ***	-0.41	2.29	2.89	5.2 ***	-0.46	2.34	2.42
Santo Domingo	1.84	-0.27	2.02	1.05	2.07	-0.32	2.13	1.12	1.96	-0.36	2.22	1.05	0.68	-0.41	2.29	0.48	1.04	-0.46	2.34	0.64
Imbabura	-0.12	-0.27	2.02	0.07	0.01	-0.32	2.13	0.16	-0.29	-0.36	2.22	0.04	0.04	-0.41	2.29	0.20	0.48	-0.46	2.34	0.40
Carchi	-0.58	-0.27	2.02	-0.15	-0.92	-0.32	2.13	-0.28	-0.67	-0.36	2.22	-0.14	-0.98	-0.41	2.29	-0.25	-0.39	-0.46	2.34	0.03
Esmeraldas	2.31	-0.27	2.02	1.28	0.31	-0.32	2.13	0.30	1.15	-0.36	2.22	0.68	1.5	-0.41	2.29	0.83	1.33	-0.46	2.34	0.76
El Oro	1.46	-0.27	2.02	0.86	1.36	-0.32	2.13	0.79	0.72	-0.36	2.22	0.49	0.6	-0.41	2.29	0.44	1.18	-0.46	2.34	0.70
Loja	1.45	-0.27	2.02	0.85	0.82	-0.32	2.13	0.53	0.71	-0.36	2.22	0.49	0.6	-0.41	2.29	0.44	1.17	-0.46	2.34	0.69
Sucumbíos	3.61 **	-0.27	2.02	1.92	3.28 **	-0.32	2.13	1.69	3.74 **	-0.36	2.22	1.85	3.26 *	-0.41	2.29	1.60	2.5	-0.46	2.34	1.26
Orellana	2.23	-0.27	2.02	1.24	2.06	-0.32	2.13	1.12	2.57 *	-0.36	2.22	1.32	2.84 *	-0.41	2.29	1.42	2.92 *	-0.46	2.34	1.44
Guayas	1.9	-0.27	2.02	1.07	3.5 **	-0.32	2.13	1.79	4.29 **	-0.36	2.22	2.10	4.79 **	-0.41	2.29	2.27	4.09 **	-0.46	2.34	1.94
Santa Elena	3.1 **	-0.27	2.02	1.67	3.18 *	-0.32	2.13	1.64	3.04 *	-0.36	2.22	1.53	2.61 *	-0.41	2.29	1.32	3.08 *	-0.46	2.34	1.51
Manabí	3.58 **	-0.27	2.02	1.91	4.01 **	-0.32	2.13	2.03	4.49 **	-0.36	2.22	2.19	5.6 ***	-0.41	2.29	2.63	5.38 ***	-0.46	2.34	2.49
Pastaza	12.54 ***	-0.27	2.02	6.34	14.07 ***	-0.32	2.13	6.76	14.6 ***	-0.36	2.22	6.74	14.62 ***	-0.41	2.29	6.57	13.65 ***	-0.46	2.34	6.02

Notes: *, **, and *** indicate the statistical significance of the parameter at the 10%, 5%, and 1% levels, respectively.

Notes

- 1 The year 2020 has been excluded to avoid biasing the analysis by the effect of the COVID-19 pandemic.
- 2 The province of Galapagos was excluded because its island status could affect the accuracy and validity of the results.
- 3 Data processing was performed using Stata 18 software.
- 4 The georeference information used to produce the graphs was taken from the Global Administrative Areas (GADM). For further details see: <https://gadm.org/> (accessed on 11 December 2024).
- 5 Further details can be found in Appendix A to this study.

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