# Cantonal Convergence in Ecuador: A Spatial Econometric Perspective

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**Abstract**

The paper analyses the convergence process of Ecuadorian cantons during the period 2007-2012 accounting for the role of spatial spillovers through using spatial econometrics. The advantage of this technique is to provide reliable estimations because it takes into account the spatial interaction in the territory. In addition, it allows identifying clusters of cantons characterised by similar spatial patterns that can be interpreted as convergence clubs because they represent areas with similar initial conditions in the "basin of attraction" that, according to economic theory, converge to a common steady state equilibrium.

The results highlight that a convergence process is present, but it involves the cluster of most developed cantons. This opens various policy implications related to i) the capacity of cantons to take advantage from the positive dynamics of neighbours, ii) the persistence of development in some circumscribed areas, and iii) the spatial unbalanced development.

**Keywords:** Subnational convergence, Spatial Econometrics, Convergence Clubs, Ecuador.

**Jel Classification:** C21, O47, R11

## 1. Introduction

The recent economic history of Ecuador has been characterised by serious instabilities that were the result of inefficient and ineffective policies that caused structural failures whose magnitude jeopardized the achievement of higher levels of development. One of them is represented by the severe provincial disparities still persisting in Ecuador, reflected in a heterogeneous economic and social geography, which accounts for provinces with asymmetric characteristics in terms of productivity and competitiveness, as well as in terms of differentiated population and social. These asymmetries between subnational areas can inhibit the growth of domestic production and contribute to its instability, becoming a problem of circular causation that can undermine the future development of the whole country. This process of unbalanced growth justifies the implementation of compensatory territorial policies whose effects have to be tested in light of the latest progresses of economic and econometric theories. The endogenous growth theory, in particular, put emphasis in the role of spillovers in order to determine the growth pattern of an economy. These spillovers, called dynamic externalities, may have various sources and are often directly linked with agglomeration economies. In contrast with traditional localization and urbanization economies, dynamic externalities explain both the formation of urban areas and local economic development over time. Under a methodological point of view, in this paper cantonal convergence in Ecuador will be evaluated by mean of spatial econometrics, a technique that accounts explicitly the first law of geography according to which everything is related to everything else, but near things are more related than distant things (Tobler, 1970).

This concept is translated into a statistical indicator called Moran's I which relates the value of a variable to the values of the same variable in the neighbours locations. In literature it is demonstrated that socio-economic variables are strongly correlated to their relative location in space creating spatial dependence, i.e. spatial clusters with homogeneous values. Spatial dependence, which has implications for the correct estimates of the parameters in the basic regression models, will be explicitly accounted in order to estimate models that consider this evidence, reaching a double advantage: to obtain reliable results and to account for the role of space in economic growth, that, according to recent literature, cannot be neglected.

In addition, concerning the spatial heterogeneity problem, we determine spatial regimes according to Moran's I, which are interpreted as spatial convergence clubs (Ertur et al., 2006), to capture territorial polarization pattern observed in Ecuadorian cantons.

The paper is structured into four further sections. The first one deals with the concept of endogenous growth theory and spatial spillovers. The second section covers the estimation technique in presence of spatial spillovers, before proceeding to analyse the economic convergence of Ecuador. The final section consists of the conclusions and the possible policy implications.

## 2. From endogenous growth theory to spatial spillovers

Economic growth and convergence is a topic that has been widely studied by scholars in the last decades. Theoretical contributions have been based on the seminal contribution of Barro and Sala-i-Martin (1991) and Mankiw et al. (1992) and have considered the role of different factors in determining the steady state level of income per capita and in fostering growth. The models based on neoclassical assumptions, anyway, do not account explicitly for the role of geography as a crucial factor that can affect the path of growth of regions and nations. This is highlighted explicitly by Rey and Montouri (1999, page 144), who indicate that "despite the fact that theoretical mechanisms of technology diffusion, factor mobility and transfer payments that are argued to drive the regional convergence phenomenon have explicit geographical components, the role of spatial effects in regional studies has been virtually ignored". Under a theoretical point of view, these empirical evidences can be considered as a confirmation of the endogenous growth theory. According with Martin and Sunley (1998, p. 208): "there are two different types of endogenous growth theory which envisage different sorts of increasing returns: endogenous broad capital models and endogenous innovation models (Crafts, 1996). Endogenous broad capital models can be further separated into two sets: those which simply show capital investment as generating externalities, and those which emphasise human capital and relate technological change to 'learning by doing' and 'knowledge spillovers'. The second type, endogenous innovation growth theory has been labelled Schumpeterian because it emphasises the returns to technological improvements arising from deliberate and intentional innovation by producers". The summary of the characteristics of the endogenous growth models is in table 1.

Table 1 - A typology of 'New' Growth Theories

| **Type of growth theory** | **"Engine of growth"** | **Spread (basis point) (Student copulas)** |
|---|---|---|
| Endogenous broad capital | Capital investment, constant returns through capital spillovers | Cumulative divergence but shaped by government spending and taxation |
| Intentional human capital | Spillovers from education and training investment by individual agents | Dependent on returns investment, public policy and patterns of industrial and trade specialization |
| Schumpeterian endogenous innovation | Technological innovation by monopolistic producers with technological diffusion, transfer and imitation | Multiple steady states and persistent divergence. Possible club convergence and "catch up" |
| Augmented Solow neoclassical | Physical and human capital, exogenous technological process universally available | Slow and conditional convergence – with club of countries with similar socio-economic structure. |

**Source**: Martin and Sunley (1996)

The endogenous growth theory puts emphasis in the role of spillovers in order to determine the growth pattern of an economy. These spillovers, called dynamic externalities, may have various sources and are often directly linked with agglomeration economies[1]. In contrast with traditional localization and urbanization economies, dynamic externalities explain both the formation of urban areas and local economic development over time. We can recall three main theories on dynamic externalities that consider their different nature and origin. Marshall-Arrow-Romer (MAR) externalities (Marshall 1890; Arrow 1962; Romer 1986) arise from intra industry knowledge spillovers (Glaeser et al., 1992). Increased concentration of firms of the same industry within a region facilitates knowledge spillovers, which in turn increases productivity. In this sense, local monopoly benefits innovations and then promotes growth. Porter (1990) agrees with MAR theory but argues that a higher degree of local competition induces firms to innovate to remain competitive. Therefore, while for Porter externalities competition is good for economic growth, for MAR externalities it is not. Finally, contrary to MAR externalities, the so-called Jacobian externalities emphasise the inter industry knowledge spillovers (Jacobs, 1969); diversity among firms is then beneficial and competition, like for Porter externalities, is good for economic growth.

These types of externalities have an explicit spatial dimension because the intensity and magnitude of knowledge transfers depend from the proximity of firms and/or regions to which firms belong. This idea refers

[1] For a review of growth models and agglomeration see Baldwin and Martin (2004).

to the well-known first law of geography stated by Tobler (1970, that, following Ertur and Koch (2007), we can write formally by means of a standard Cobb-Douglas production function that includes spatial externalities:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \qquad \text{with } 0 < \alpha < 1 \tag{1}$$

where $Y_i$ is the output, $K_i$ is the input capital, $L_i$ is the input labour and the aggregate level of technology $A_t$ is defined as follows:

$$A_{it} = \Omega_t k_{it}^{\theta} \prod_{j \neq i}^{N} A_{ji}^{\rho W_{ij}} \tag{2}$$

where $\Omega_t = \Omega_0 e^{\mu t}$ is the common stock of knowledge which grows at rate $\mu$. This factor reflects the knowledge progress due to the belonging to a given group of country. The technology level $A_{it}$ is given by two additional terms: physical capital and the stock of knowledge in the neighbouring regions. The weight of the physical capital is determined by $\theta$, varying between 0 and 1. The exponent $W_{ij}$, is the spatial weight matrix which measures the strength of proximity of each pair of locations and that will be explained in detail in the following section. Finally, the scalar $\rho$ determines the strength of the technological spatial spillovers due to the proximity to other regions and it is assumed to vary between 0 and 1.

## 3. Econometric estimation of spatial spillovers

*Spatial weights matrix*

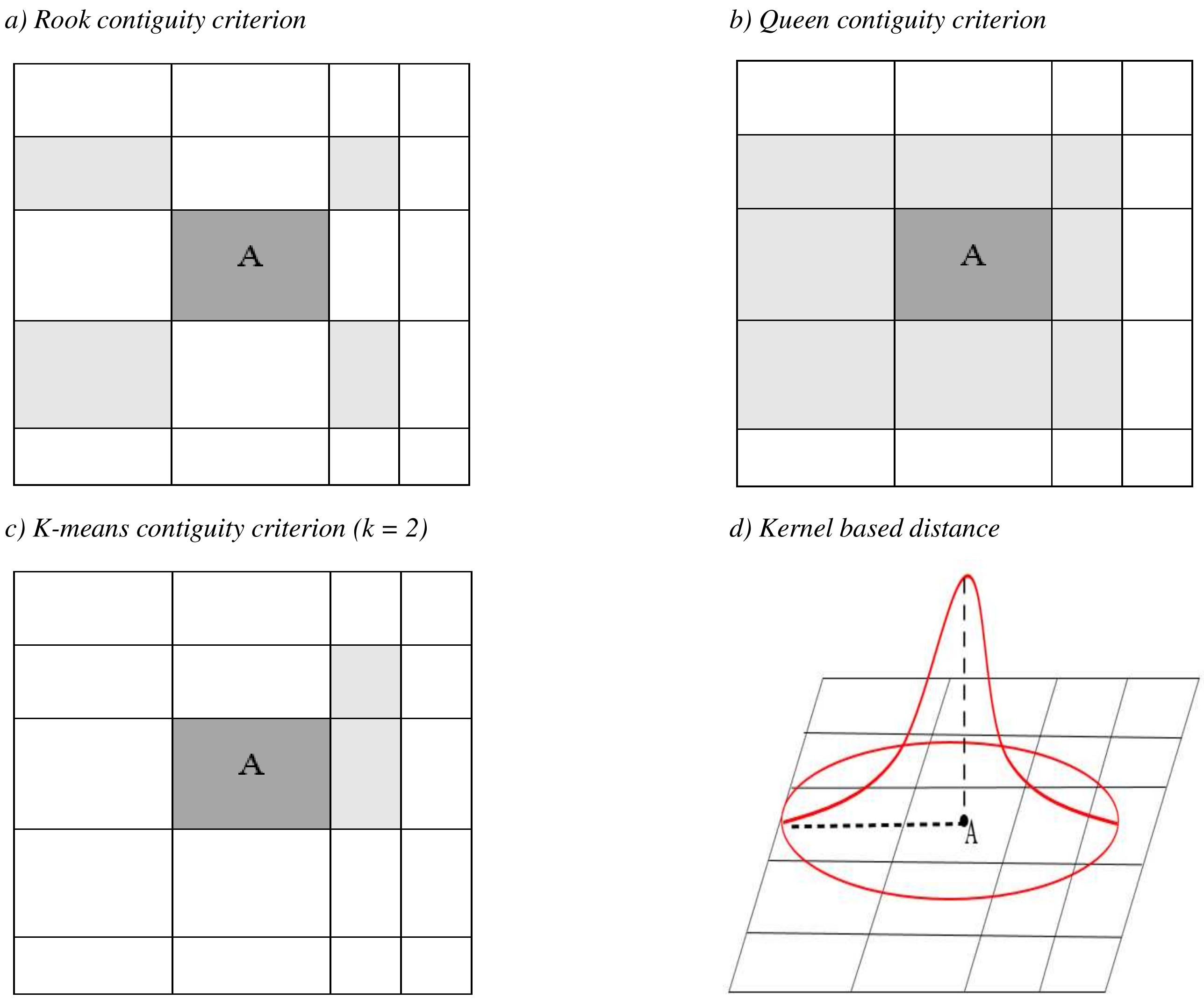
The "degree" of advantage that a region can take from spatial spillovers depends from its relative spatial location, i.e. from the average distance from other regions, which is fundamental to measure the possibility of diffusion of the knowledge process. In this extent, as recalled by the first law of geography, the definition of distance is crucial. According to literature, the notion of distance can refer to a wide range of alternative definitions that can be classified into three main categories:

- Physical distance: based on the physical characteristics of a territory;
- Socioeconomic distance: based on the cultural or economic closeness of some territories;
- Mixed physical-socioeconomic distance: based on a weighted mixture of the two previous concepts.

Physical distance has various dimensions. Among the most used there are Rook and Queen criterion (figure 1a and 1b) which consider two locations as neighbours if they have at least a border and a point in common, respectively. Then, we have k-means criterion (figure 1c) where the number of closest neighbours is fixed *a priori* and the kernel based distance[2] (figure 1d) in which the neighbours are weighted in function of their physical distance (in linear or route kilometres, miles or travel time) from the study region[3].

[2] The most common kernels are the Gaussian function $w_{ij} = exp\left(-0.5 \times d_{ij}^2/h_{ij}^2\right)$ and the modified bi-squared function $w_{ij} = \left[1 - \left(d_{ij}^2/h_{ij}^2\right)\right]^2$, accounting only for the $N$ closest neighbours whose distance $h_{ij}$ is smaller than the threshold distance $d_i$. Otherwise $w_{ij} = 0$ .

[3] In the case of k-means and Gaussian criterion, the distance is calculated with respect to the centroids of the polygons. The centroid or geometric center of a two-dimensional region is the arithmetic mean, or average, position of all the points in the shape.




**Source**: authors' elaboration.

Figure 1 - Physical distance

Socioeconomic distance is little used in economic analysis. We can recall the studies of Moreno and Lopez-Bazo (2007) and Pontarollo and Ricciuti (2015) who adopt a distance based on the inverse of the absolute difference between the population density as a proxy for agglomeration economies of each pair of regions. The idea is that the more similar the economies of two locations are, the greater their weights.

More emphasis is put in the distance conceived as a mix of physical and socio-economic factors. The typical function is of the form:

$$\begin{cases} w_{ij} = y^{\alpha} d_{ij}^{-\gamma} & \text{if } d_{ij} < h_{ij} \\ w_{ij} = 0 & \text{if } d_{ij} \geq h_{ij} \end{cases} \tag{3}$$

Where $y$ is a socio-economic variable referred to the neighbour region (Fingleton, 2001; Moreno and López-Bazo, 2007), or an interaction between variables (Montresor et al., 2011). The variable $d_{ij}$ is a measure of geographical separation of locations $i$ and $j$ and $h_{ij}$ is the threshold distance. The coefficients $\alpha$ and $\gamma$ reflect the weight attributed to $y$ and $d_{ij}$, with $\alpha = 0$ corresponding to a pure distance effect, and $\gamma = 0$ corresponding to a pure economic size effect. The difficulties to estimate these coefficients makes practical sense to assign values to these coefficients a priori. Examples of this approach are in LeSage and Pace (2008), Fingleton and Le Gallo (2008) and Arbia et al. (2010).

Once the distance is defined, a squared connectivity matrix in which the diagonal is put equal to zero by convention, such as a region is not a neighbour of itself, is created. In the other cells, zero is put in the case in which a region is not a neighbour of another and 1, or the appropriate weight, vice versa. The resulting matrix is then generally standardized by row to 1, takes the name of spatial weight matrix and it is conventionally written as $W_{ij}$.

In order to summarise, the concept of spatial weights matrix is rather complex and still debated in literature because i) the concept of neighborhood is not unique and ii) the widely accepted choice to use binary weight scheme does not include information such as the degree of proximity and/or of dissimilarity among regional economies. The strength of the spatial spillovers, then, is due to the linkage path determined by $W_{ij}$ that, in empirical investigations, has to be deeply understood and related to the particular context of analysis.

*Exploratory Spatial Data Analysis (ESDA)*

The Exploratory Spatial Data Analysis is used to measure the strength of spatial dependence. The most known is the Moran's I (*MI*) (Moran, 1950). The Moran's I, basically, relates the value of a selected variable with its spatial lag, i.e. the value of the same variable in the neighbour areas, and it is defined as:

$$MI = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(x_i - \bar{x}\right)\left(x_i - \bar{x}\right)}{\sum_i \left(x_i - \bar{x}\right)} \tag{4}$$

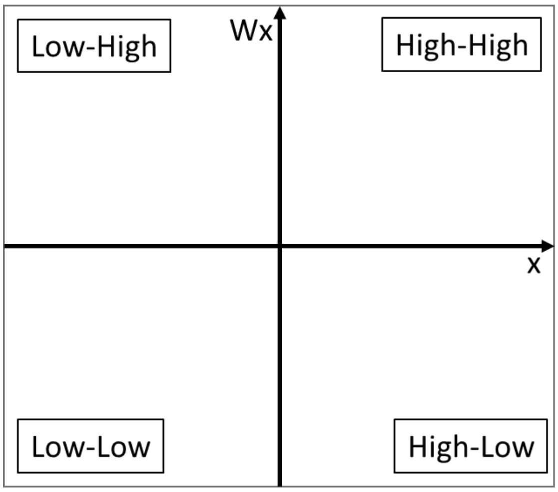
where $N$ is the number of spatial units indexed by $i$ and $j$; $x$ is the variable of interest; $\bar{x}$ is the mean of $x$; and $w_{ij}$ is an element of a matrix of spatial weights matrix $W_{ij}$.

The expected value of Moran's $I$ under the null hypothesis of no spatial autocorrelation is

$$E(MI) = -1/(N-1) \tag{5}$$

The calculated Moran's I for global autocorrelation varies between -1 and 1. A positive coefficient corresponds to a value of Moran's I that is larger than its theoretical mean of –1/N-1, or, equivalently, a positive z-value, and points to positive spatial autocorrelation, i.e. cluster of similar values can be mapped. The reverse represents regimes of negative association, i.e. dissimilar values clustered together in a map. A zero value indicates a random spatial pattern. For statistical hypothesis testing, Moran's $I$ values can be transformed to $Z$-scores in which values greater than 1.96 or smaller than −1.96 indicate spatial autocorrelation that is significant at the 5% level.

The advantage of this statistic is that it can be visualised on a scatterplot, the so-called Moran scatterplot (figure 2), in which the spatial lag of the (standardized) variable is on the vertical axis and the original (standardized) variable is on the horizontal axis. Thus, each of the points in the scatterplot represents a combination of a locations' value and its corresponding spatial lag.




**Source**: authors' elaboration.

Figure 2 - Moran Scatterplot

The x- and y-axes divide the scatterplot into 4 quadrants (anticlockwise from top right): in the first and third (high-high, HH, and low-low, LL, respectively) a location that exhibits a high (low) value of the variable is surrounded by locations with a high (low) value of the variable as well. In the second and fourth (low-high: LH and high-low: HL, respectively) a location that with a low (high) value of the variable is surrounded by location with a low (high) value of the variable. A concentration of points in the first and third quadrants means that there is a positive spatial dependence (that is, nearby locations will have similar values), while the concentration of points in the second and fourth quadrants reveals the presence of negative spatial dependence (that is, nearby locations will have dissimilar values).

*Spatial regressions*

The problem with classical empirical analyses that ignore the influence of spatial location on the process of growth is that they may produce biased results and hence misleading conclusions. To address this problem, some regional economists and economic geographers suggest accommodating spatial heterogeneity and dependence in regional growth specifications. Spatial dependence have implications for the estimates of the parameters in the basic regression models. In particular, if spatial structure is in the residuals of an Ordinary Least Squares (OLS) regression models, this will lead to inefficient estimates of the parameters, which in turn means that the standard errors of the parameters will be too large. This lead to incorrect inference on significant parameter estimates. When spatial structure is in the data, the value of the dependent variable in one spatial unit is affected by the independent variables in nearby units. In this case the assumption of uncorrelated error terms as well as of independent observations is also violated. As a result, parameter estimates are both biased and inefficient. Some authors, then, explicitly included spatial effects in growth models.

The model that accounts for spatial dependence in the dependent variable is called spatial lag and its cross-section specification is as follows:

$$y_i = \rho W y_i + \alpha + \psi X_i + u_i \qquad \text{with } u_i \sim i.i.d(0, \sigma^2) \tag{6}$$

where on the left hand side (LFS) of Eq. (6) we have the dependent variable $y_i$, and, on the right hand side (RHS) a set of additional explanatory variables $X_i$ and the spatial lag of the dependent variable, $Wy_i$ and the associated parameter $\rho$ to be estimated. The spatial lag specification includes the fact that the variable in each location, for example economic growth, is potentially affected by the same variable in its neighbours. Rewriting in matricial form for convenience we have:

$$\mathbf{Y} = (\mathbf{I} - \rho\mathbf{W})^{-1}[\alpha\mathbf{I} + \mathbf{X}\boldsymbol{\psi} + \mathbf{u}] \tag{7}$$

where $\mathbf{Y}$ is a $1$-by-$n$ vector, and $\mathbf{X}$ is the $k$-by-$n$ matrix of additional explanatory variables and $\boldsymbol{\psi}$ is the vector of coefficients.

So the expected value of $\mathbf{Y}$ is:

$$E[\mathbf{Y}] = (\mathbf{I} - \rho\mathbf{W})^{-1}[\alpha\mathbf{I} + \mathbf{X}\boldsymbol{\psi}] \tag{8}$$

since the errors all have mean zero. The inverse matrix term is called spatial multiplier, and indicates that the expected value of each observation $\mathbf{Y}$ will depend on a linear combination of X-values taken by neighbouring observations, scaled by the dependence parameter $\rho$. The presence of the autoregressive parameter $\rho$ makes the estimation of Eq. (6) by OLS inconsistent (Anselin, 1988). This implies that a maximum likelihood approach has to be used:

$$\ln L(\rho, \psi, \sigma^2) = -\frac{N}{2}\ln 2\pi - \frac{N}{2}\ln\sigma^2 + \ln|\mathbf{I} - \rho\mathbf{W}| - \frac{1}{2\sigma^2}\mathbf{u}'\mathbf{u} \tag{9}$$

where $\mathbf{u} = (\mathbf{I} - \rho\mathbf{W})\mathbf{Y} - [\alpha\mathbf{I} + \mathbf{X}\boldsymbol{\psi}]$

where $N$ is the number of observations and $|\mathbf{I} - \rho\mathbf{W}|$ stands for the determinant of the matrix. The parameters with respect to which this likelihood has to be maximised are $\rho$, $\boldsymbol{\psi}$ and $\sigma^2$.

The interpretation of Eq. (6) is not straightforward for the presence of the autoregressive parameter; at this regard it is convenient using the matrix notation (7) to consider the asymptotic expansion of the inverse relationship of the spatial multiplier (Debreu and Herstein, 1953):

$$(\mathbf{I} - \rho\mathbf{W})^{-1} = \mathbf{I} + \rho\mathbf{W} + \rho^2 W^2 + \rho^3\mathbf{W}^3 + \ldots + \rho^N\mathbf{W}^N \tag{10}$$

that makes possible to rewrite Eq. (7) as follows:

$$\mathbf{Y} = (\mathbf{I} + \rho\mathbf{W} + \rho^2 W^2 + \rho^3\mathbf{W}^3 + \ldots + \rho^N\mathbf{W}^N)[\alpha\mathbf{I} + \mathbf{X}\boldsymbol{\psi} + \mathbf{u}] \tag{11}$$

where we have a direct effect when the term $\mathbf{I}$ in the first parenthesis of the RHS of Eq. (11) is multiplied by the terms in the second parenthesis. In this case the interpretation, like in the OLS models, is the partial derivative of independent variable with respect to dependent. The first order indirect effect, $\rho\mathbf{W}$, is the effect due to a change in the values of the variables in the contiguous areas; the second order indirect effect, $\rho^2\mathbf{W}^2$ is due to a change of the independent variable in the neighbour of the neighbour regions[4], and so on. Accordingly,

[4] Note that a region is also a neighbor of itself, so $\mathbf{W}^2$ has positive elements in the diagonal.

as noted by Anselin (2003), the spatial structure in (6) is related to the presence of global externalities. A shock in a region *i* is transmitted to its neighbours by parameter $\rho$ that, in turn, through the spatial weights matrix **W**, is transmitted again to region *i*, reinitiating the process until the effect becomes negligible for *N* that tends to infinite.

Another widely used model is the spatial error:

$$y_i = \alpha + \psi X_i + u_i \qquad u_i = \lambda W u_i + v_i \qquad \text{with } u_i \sim i.i.d(0, \sigma^2) \tag{12}$$

or, alternatively, in matrix form:

$$\mathbf{Y} = \alpha\mathbf{I} + \beta\mathbf{y} + \mathbf{X}\boldsymbol{\psi} + \left(\mathbf{I} - \lambda\mathbf{W}\right)^{-1}\mathbf{v} \tag{13}$$

with the complete error variance–covariance:

$$E\left[\mathbf{v}'\mathbf{v}\right] = \sigma^2\left(\mathbf{I} - \lambda\mathbf{W}\right)^{-1}\left(\mathbf{I} - \lambda\mathbf{W}\right)^{-1} \tag{14}$$

The spatial error model has an expectation equal to that of the standard regression model. While in large samples estimates for the parameters and OLS regression will be the same, in small samples there may be an efficiency problem if spatial dependence in the error terms is not correctly specified.

Spatial error model is estimated through Maximum Likelihood like spatial lag model (Anselin, 1988). Assuming normality for the error terms, and using the concept of a Jacobian for this model as well, the log-likelihood can be obtained as:

$$\ln L\left(\lambda, \psi, \sigma^2\right) = -\frac{N}{2}\ln 2\pi - \frac{N}{2}\ln\sigma^2 + \ln\left|\mathbf{I} - \lambda\mathbf{W}\right| - \frac{1}{2\sigma^2}\mathbf{v}'\mathbf{v} \tag{15}$$

where $\mathbf{v} = \left(\mathbf{Y} - \left[\alpha\mathbf{I} + \mathbf{X}\boldsymbol{\psi}\right]\right)\left(\mathbf{I} - \rho\mathbf{W}\right)$

In this case, a random shock in region *i* affects the growth rate in that region and additionally impacts all the other regions through the spatial transformation (Fingleton and López-Bazo, 2006). As a result, model (14) recognises the presence of global externalities associated solely with random shocks (Anselin, 2003), and the partial derivative are equivalent to a standard OLS regression.

Starting from Eq. (14), it is possible to develop the spatial multiplier $(\mathbf{I} - \lambda\mathbf{W})^{-1}$ in order to obtain a model with the spatial lag of both dependent and independent variables (LeSage and Pace, 2009), called spatial Durbin model. The unconstrained model is as follows:

$$y_i = \rho W y + \alpha + \psi X_i + \varphi W X_i + u_i \tag{16}$$

with $u_i \sim i.i.d(0,\sigma^2)$

As noted by LeSage and Fischer (2008), the spatial error model used in many spatial growth studies can arise only if there are no omitted explanatory variables, or if these are not correlated with included explanatory variables, both of which seem highly unlikely circumstances in applied practice.

The interpretation of the spatial Durbin model is analogous to the spatial lag model, but in this case we have that the indirect effect is due both to the lag of the dependent and independent variables.

The last model, largely neglected by spatial econometricians, but of extreme interest because it is able to account for local spillover effects, is the spatial lag of X (SLX) model. SLX model includes only the lag of the independent variables and it is defined as follows:

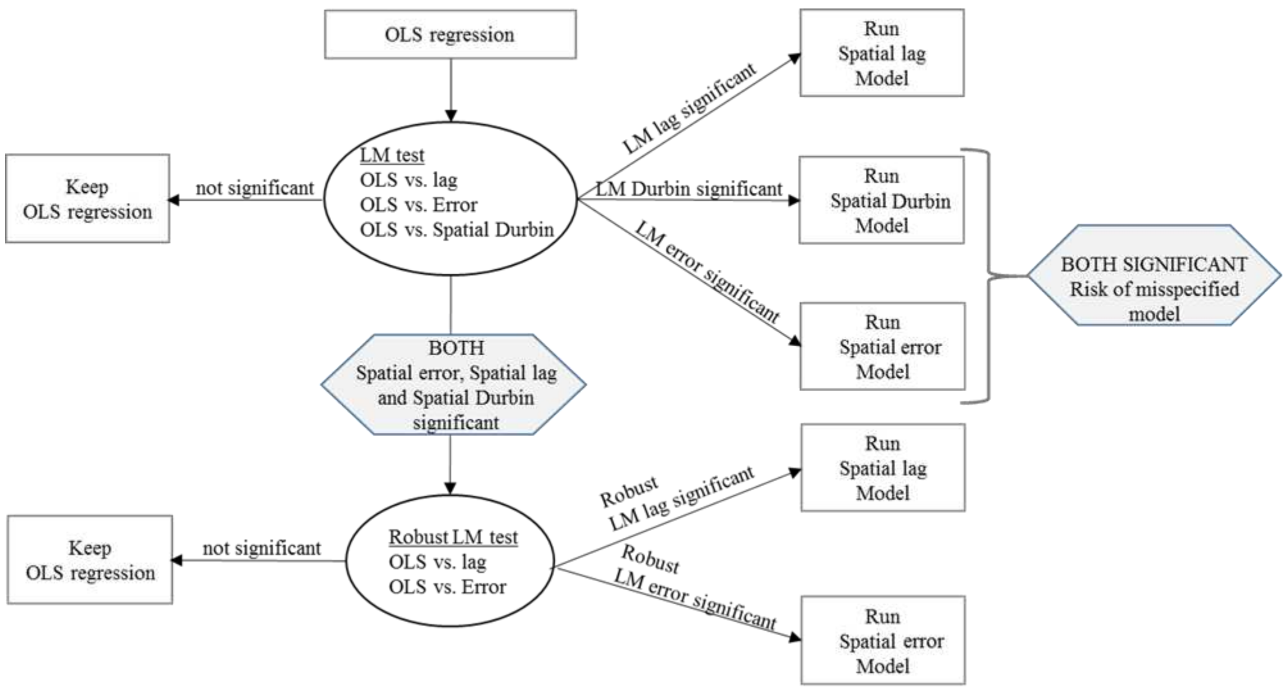
$$y = \alpha + \psi X_i + \varphi W X_i + u_i \qquad (17)$$

with $u_i \sim i.i.d(0,\sigma^2)$

The estimation methodology is the classical OLS and the marginal effects are like usual. The peculiarity of this model is that it does not account for global spillovers, but for local ones. Global spatial multiplier of spatial lag and spatial Durbin models, on the other hand, requires that regions are rather homogeneous within each cluster, i.e. regions in the cluster with high (low) values have to be surrounded by others with pretty similar values. This precondition allows that the economic shocks spread over a large area self-reinforcing themselves because of the similar characteristics of the regions in that area. The similarity, in the case of growth regressions, has to be in the average regional growth rate that requires that their economic structure and interrelations are quite strong. The main evidences of the existence of global spillovers are in Europe, where the regions are very homogeneous and well as integrated (under the point of view of infrastructure, trade, commuting, technology, etc.) within the cluster of richer regions (centre and north) and poorer ones (Mediterranean regions) Ertur et al. (2006).

The choice between spatial models can follow two approaches: a specific-to-general approach and a general-to-specific approach.

In the first case (figure 3) the selection between the spatial lag and spatial error model is done through a (robust) Lagrange Multiplier (LM) test (Anselin and Rey, 1991 and Florax and Folmer, 1992) performed on OLS estimates. Nevertheless, as recently observed by López-Bazo et al. (1999) and Fischer and LeSage (2008), the choice of spatial error model could hide misspecification problems that can lead not only to inefficient estimations, but also to biased results. In this case, a solution proposed by LeSage and Pace (2009), is to choose the spatial Durbin model, especially LM test for spatial Durbin is significant too, On the other hand, Elhorst (2010) suggests that if LM tests for spatial lag and error both significant, the next step should be to estimate the spatial Durbin model.

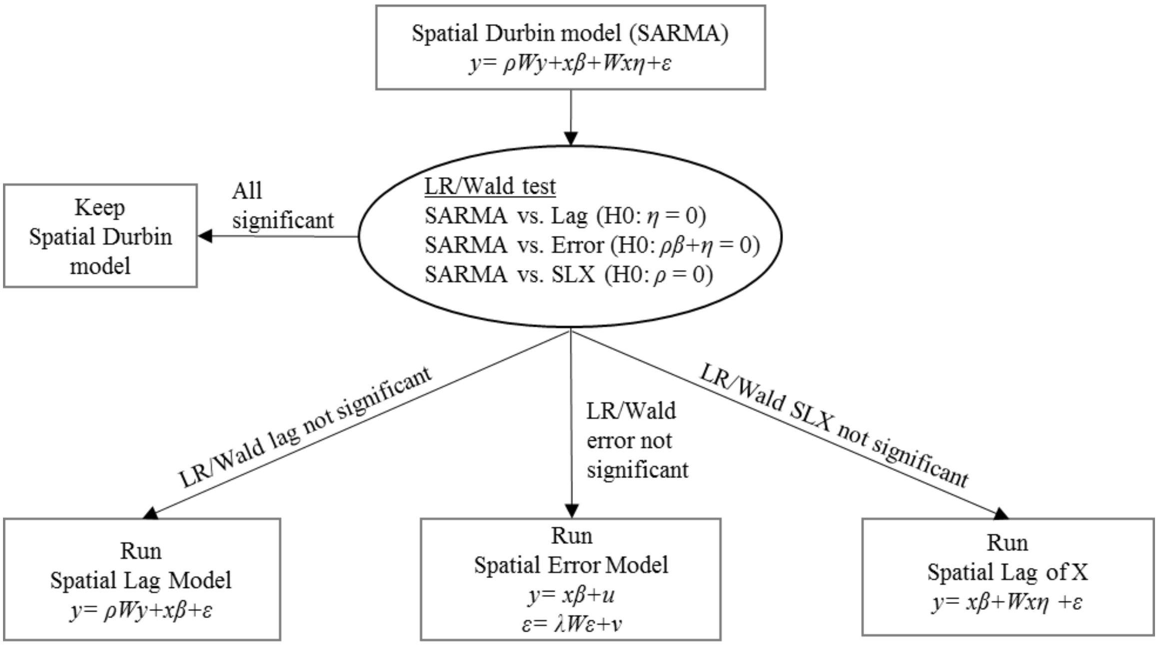



**Source**: authors' elaboration.

Figure 3 - Specific-to-general approach

The second approach, the general-to-specific (figure 4), is highly suggested by (LeSage and Pace, 2009). In this case, a Lagrange Ratio (LR) and a Wald test are performed to investigate whether spatial Durbin model (with spatial lag of both dependent and independent variables) can be simplified to a spatial lag, spatial error model (Mur and Angulo, 2006) or SLX model.

The two approaches have to be followed in parallel. The possibility that in the specific-to-general case the Spatial Durbin model is selected has to be further investigated in particular if the LM test points that spatial error model is the right model too. In this case a possible misspecification problem might arise and the general-to-specific approach helps to overcome this problem.



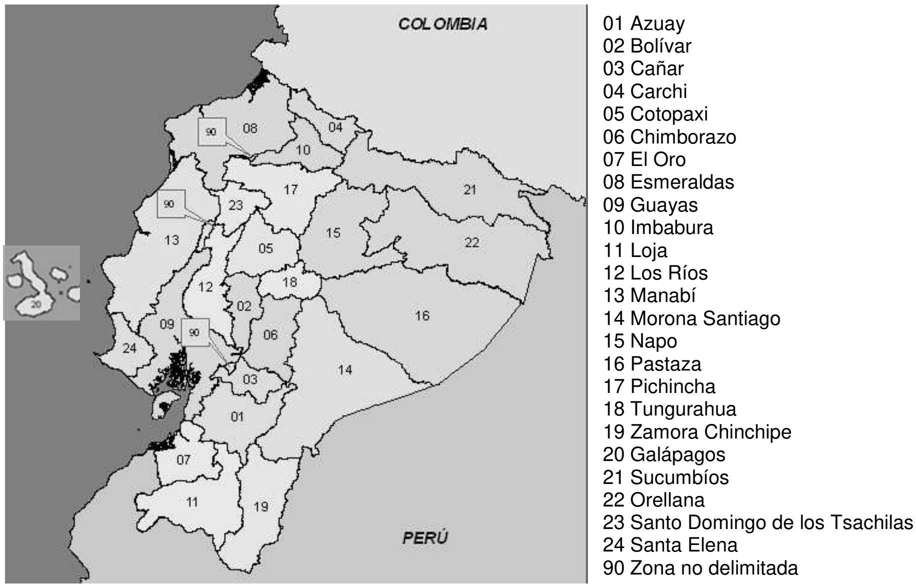

**Source**: authors' elaboration.

Figure 4 - General-to-specific approach

## 4. Empirical estimation: the case of Ecuador

With an area of 283,500 square kilometres, the Republic of Ecuador is divided into 24 provinces, 221 municipalities (also called cantons) and 1,228 parishes, with around 16 million inhabitants.

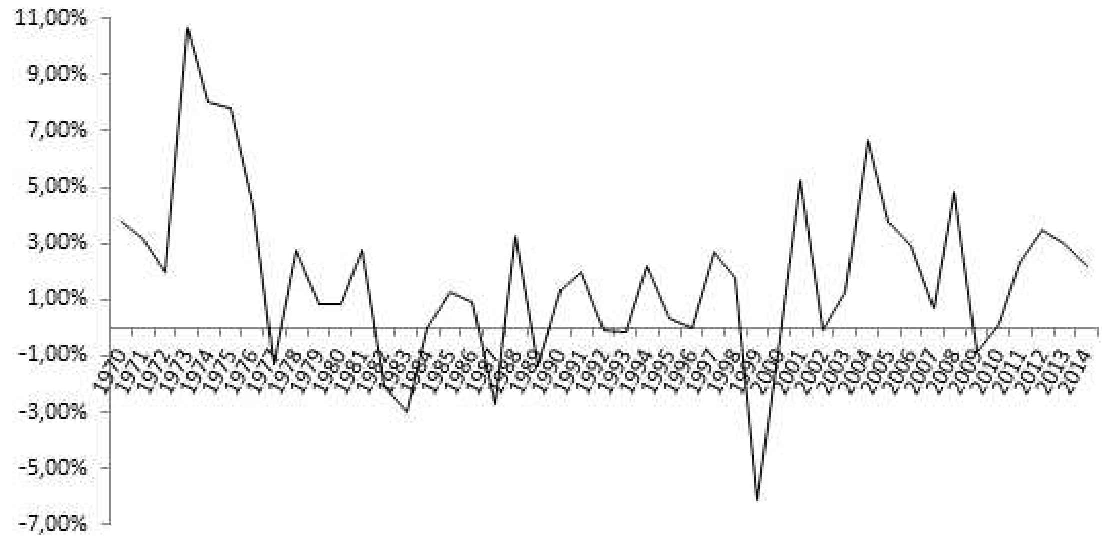
The recent history of Ecuador is characterised by severe economic downturns (Figure 6), which have been accompanied by political, social and institutional instability, and associated with the volatility of prices and production of oil, the main export product from 1974. This instability has caused a territorial heterogeneity, with profound economic and social subnational asymmetries (Mendieta, 2015a, Alvarado, 2011; CEPAL, 2009).




**Source**: authors' elaboration on the basis of INEC.

Figure 5 - Provinces of Ecuador

During the eighties and nineties in Ecuador, as in many Latin American countries, we had the implementation of a series of policies and reforms with the stated aim to decentralise and make more autonomous the management of development policies, aimed at increasing fiscal transfers to provincial and municipal governments, together with certain administrative powers (Carrión et al., 2007). This moment of decentralisation coincides with neoliberal policies, which characterised the moment of instability that Ecuador lived in those decades. This, combined with the marked economic and social differences between subnational regions explains the limited benefit that these decentralisation policies obtained in terms of reduction of asymmetries (Barrera, 2007).




**Source**: authors' elaboration on the basis of INEC.

Figure 6 - Annual rate of GDP per capita growth in Ecuador: period 1970-2014.

In 2008, with the came into force of the new Constitution, decentralisation had another push. This process is coordinated by the National Secretariat of Planning and Development (SENPLADES), which promotes decentralisation of governance, and seeks to expand local capacity for autonomy and development within the framework of the objectives of the National Plan for Good Living (PNBV). Finally, by the end of 2010, it has come into force the Code of Land Management, Autonomy and Decentralization (COOTAD, 2010), which contains a number of institutional mechanisms for expanding the opportunities and responsibilities of different local institutional levels: regions, provinces, municipalities and parish councils.

This decentralisation process implied, in recent years, an unprecedented level of public investment deployed throughout the country, especially on roads, hydroelectric projects and in various areas among which health, education, which was made possible thanks to the significant government revenues derived mainly from high oil prices and a more efficient tax collection. The effects of these actions and strategies begin to show their effects in terms of poverty reduction (Mideros; 2012) and economic growth (Martin, 2012), but, given the severe structural problem inherited from the past, they still do not give grounds to a lasting reduction of local economic disparities (Mendieta 2015b).

The issue of subnational convergence and balanced territorial growth, then, is an actual and debated topic, which this study will analyse under the perspective of spatial econometrics, which is able to give some insights with respect to the role of space into economic development.

The analysis of convergence regarding the Ecuadorian case starts with the exploratory spatial data analysis of 214 cantons[5] over the period 2007-2012 using data from the National Statitical and Census Institute (INEC). The first step consists in an Exploratory Spatial Data Analysis based on a Queen contiguity matrix where the islands have been connected to Guayaquil canton[6]. Then we standardised the matrix by row. This allows to read the spatial lag as a weighted average of the values of the variables in the neighbour cantons.

Figure 7 shows the Moran scatterplot (in the right side) and the map of the quadrants (in the left side) of Gross Value Added per person in 2007, in 2012 and of its growth over that period. The information that we have from this figure is that the concentration of cantons with similar values is not very strong, but highly statistically significant. In 2007 the Moran's I is 0.19 (p-value < 0.001). The clusters of cantons with the highest GVA per capita are around Guayaquil and in the provinces of Azuay, El Oro, Pichincha, Santo Domingo, Galapagos and in the south of Napo. Despite the rather strong and homogeneous concentration, the low Moran's I is due to the presence of many "border" cantons, located between the cluster high-high (first quadrant) and low-low (third quadrant). These cantons are extremely interesting because they correspond to a situation in which a low-developed area is surrounded by well-developed ones (second quadrant), or a well-developed area is surrounded by low developed ones (fourth quadrant). In the first case it is important that the low-developed cantons take a benefit from the favourable context, and then that the spillovers from richer

[5] We excluded the cantons of Putumayo, Shushufindi, Cuyabeno, Orellana, La Joya, De Los Sachas, Las Golondrinas, El Piedrero, Sevilla De Oro, Quinsaloma and Manga Del Cura for the absence of data of because they are outliers in which the GVA is given by mining.

[6] In principle, it is possible to use spatial weights matrices with location without neighbours, but it is not generally used in literature because it complicates the interpretation of results and because the islands are not unconnected from the continent under a socio-economic point of view.

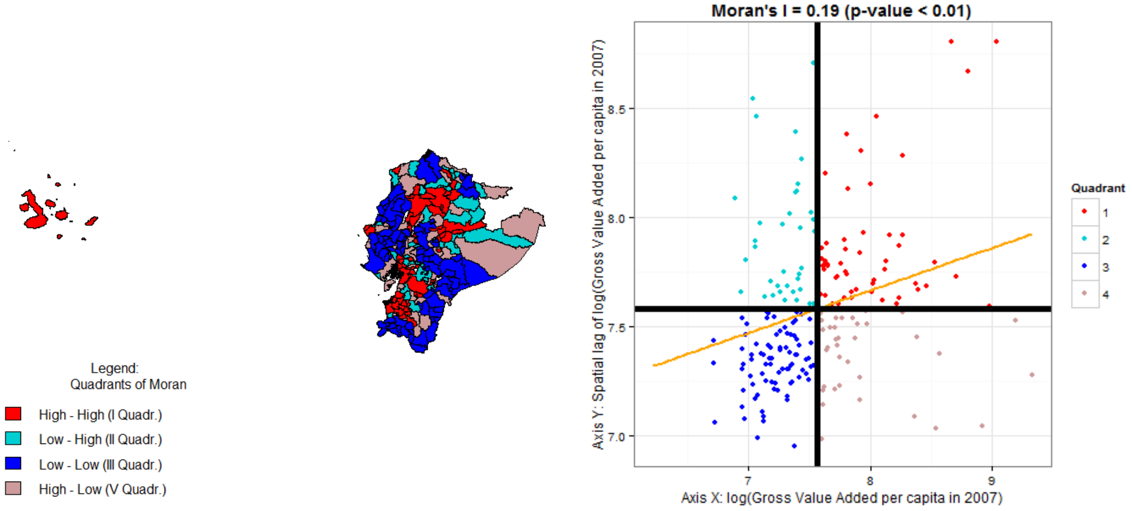
cantons spread over the weaker, increasing their Gross Value Added per capita. Under a policy point of view, the challenge is to exploit the growth potential of lagging areas through the surrounding territorial context as a driver for growth. This clearly requires a cluster perspective and common shared objectives between territorial actors (see Ketels, 2013). The second case consists in developed cantons surrounded by lagging ones. In this situation, the main problem is to make possible that the direction of the spillovers will be from the stronger area to the weaker ones, and not vice-versa, which would mean depressing the developed cantons. The difficulty, then, is, first, to avoid that a strong canton will fall at the level of the surrounds cantons; second, create policy interventions able to support the level of wealth of developed areas without leaving aside the lagging ones.

Figure 7b corresponds to figure 7a, but in 2012. The situation does not strongly change. The only difference is that some cantons in the provinces of Napo, Pastaza and Orellana, form "border" cantons in 2007 become part of the high-high quadrant and that some cantons in the province of El Oro from the first quadrant shifted to the second.

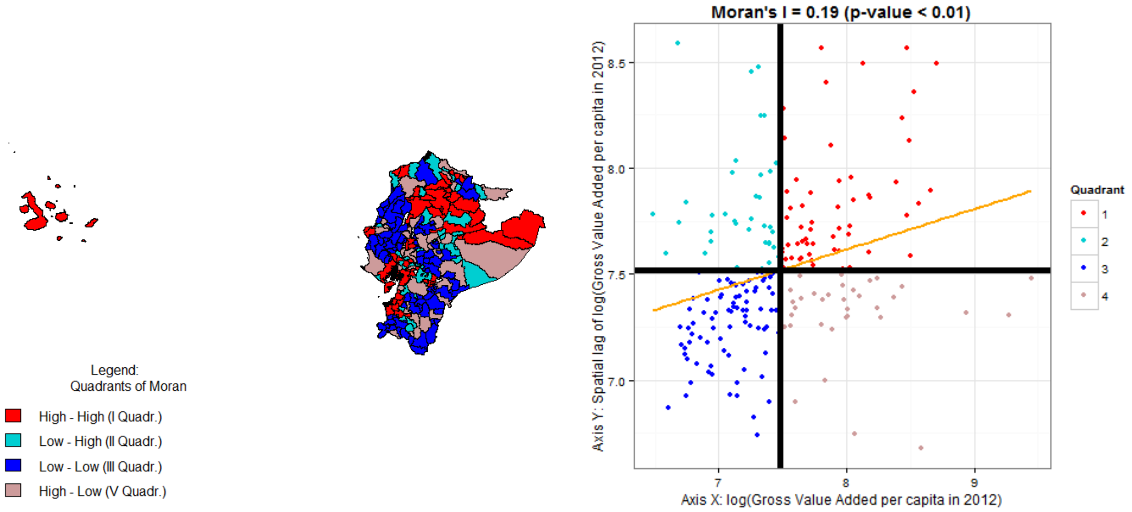
Figure 7c, finally, shows the average growth of Gross Value Added per person between 2007 and 2012. The clusters of cantons with higher growth roughly correspond to the provinces of Napo, Pastaza and Orellana, Pichincha, Guayas, Imbabura and Zamora, showing that cantons that converge do not always correspond to the less developed. This probably justify also the increasing observed inequality which raised of 17% between 2007 and 2012.[7]

[7] Variance, as customary, of computed over the log of GVA per person

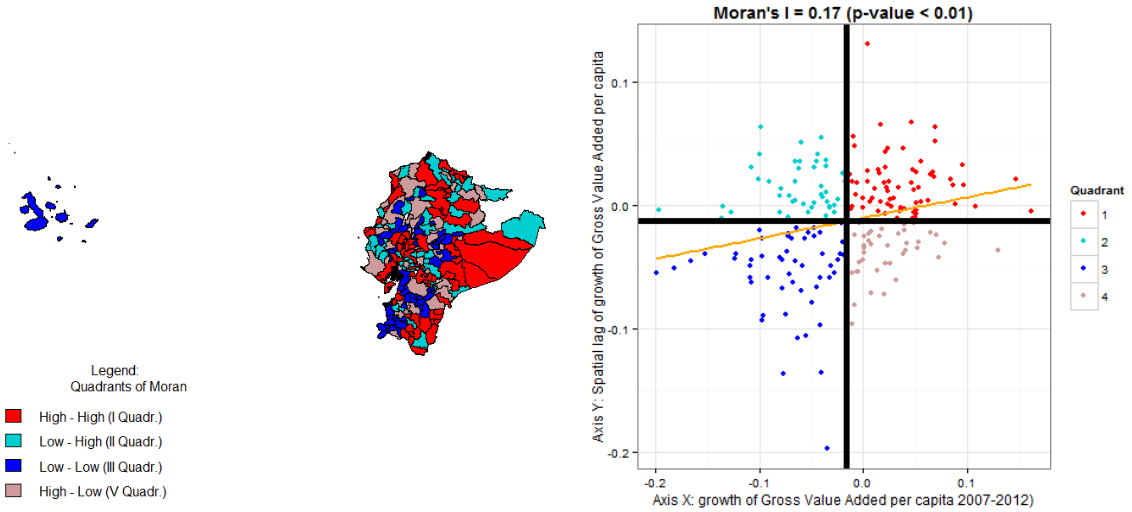
*a) Gross Value Added per person in 2007*




*b) Gross Value Added per person in 2012*




*c) growth of Gross Value Added per person in 2007-2012*




**Source**: authors' elaboration on the basis of INEC.

Figure 7 - Moran clusters and scatterplot

The first exploratory analysis gave us some insights about the territorial dimension of the GVA per person between 2007 and 2012 and of its growth, but a more refined analysis has to be done via regression analysis that, following Barro and Sala-i-Martin (1991), is defined as follows:

$$\frac{1}{T}\ln\left(\frac{y_{iT}}{y_{i0}}\right)=\alpha+\beta\ln\left(y_{i0}\right)+\psi X_i+u_i \qquad \text{with } u_i \sim i.i.d(0,\sigma^2) \qquad (18)$$

where on the left hand side (LFS) of Eq. (18) we have the average growth of GVA per capita between period *0* and *T*, and, on the right hand side (RHS) its initial level, $y_{i0}$, and a set of additional explanatory variables $X_i$. In the case in which the parameter $\beta$ is statistically significant and negative, the convergence hypothesis holds: the poor economies tend to grow faster that the richer ones. Finally, $\alpha$ is a constant, and $\psi$ a parameter to be estimated. In the case in which no additional variables $X_i$ are added to the model or if they are not statistically significant there is absolute convergence, that means that all cantons converge to the same steady state. Absolute convergence requires that all cantons have the same production function and have access to the same technology, which requires a homogeneous and well-connected socio-economic context.

Contrary to absolute convergence, we have conditional convergence in which the equilibrium differs across cantons, and each one approaches its own but unique, globally stable, steady state equilibrium because each one has its own production function and factors affecting long run growth. A third possibility accounts for the existence of club convergence (Durlauf and Johnson, 1995), a concept related with the heterogeneity problem due to economic polarization, persistent poverty, and clustering. Club convergence is based on endogenous growth models and accounts for the possibility of multiple, locally stable, steady state equilibria in which the different equilibria depends on both structural characteristics and initial conditions. Economies converge to a common steady state if the initial conditions are in the "basin of attraction" of the same steady state equilibrium. When convergence clubs exist, one convergence equation should be estimated per club, corresponding to different regimes.

The standard OLS estimation of Eq. (18), which is in table 2, shows that convergence is statistically significant and the rate[8] is around 2.72%. This confirms the findings of figure 7, but the probability that only absolute convergence is present is rther low because Ecuador is a heterogeneous and quite polarised context where there are various peripheral and unconnected cantons in which industrialisation level is still very low. The second motivation that leads to exclude the absolute convergence is the low R squared that means that the regression is misspecified.

At this regard, the aim of our analysis is not to deepen the analysis of the additional factors affecting the convergence path of Ecuadorian cantons, but to focus more in the application of the econometric technique. Anyway, it is necessary to highlight the limitations of our study, that we intend to overcome in the future with other more comprehensive framework.

[8] The speed of convergence is calculated as: $\frac{-\left(1-e^{\beta T}\right)}{T}$

Table 2 - OLS estimate

| Variable | |
|---|---|
| Constant | 0.177 (0.067) *** |
| log(GVA/person) | -0.025 (0.009) *** |
| AIC | -580.945 |
| $R^2$ (adj.) | 0.038 (0.033) |
| F-test (p-value) | 8.410 (< 0.01) |
| Moran's I on residuals (p-value) | 0.167 (< 0.01) |
| Breush Pagan test (p-value) | 8.052 (< 0.01) |

*Significant at 1%, ** significant at 5%, *** significant at 10%. Standard error in brackets.

**Source**: authors' elaboration on the basis of INEC.

In table 2 we observe that the Moran's I is very significant pointing that the spatial dependence in residuals is present. Breush Pagan test on heteroskedasticity is significant too because the error variance could well be affected by the spatial dependence in the data. This implies that, in presence of spatial autocorrelation, tests for heteroscedasticity, in reality, reveal autocorrelations too. This implies that we need further investigation in order to understand which type of spatial regression is the most appropriate. The results of the specific-to-general approach is shown in table 3. According to the LM tests we have that both spatial lag and spatial error models are eligible. This requires the robust versions of LM tests that excludes both spatial models. The test for Spatial Durbin, anyway, is the most significant leading to the choice of this model. The problem related to this outcome is that, as the spatial Durbin can be a derivation of spatial error model, it can be the best choice simply because it accounts for the possible misspecification of the estimated regression, a highly possible situation for what we explained in the previous section and for what shown by Fischer and LeSage (2008)

Table 3 - Specific-to-general approach

| Test | |
|---|---|
| LM error | 9.899 (<0.01) |
| LM lag | 8.931 (< 0.01) |
| Robust LM error | 1.357 (0.244) |
| Robust LM lag | 0.390 (0.532) |
| LM SARMA | 10.289 (< 0.01) |

In brackets p-values.

**Source**: authors' elaboration on the basis of INEC.

The following step is to test which is the best model according to the general-to-specific approach (table 4). We can surely exclude that the spatial Durbin model can be simplified to SLX model because it is the only significant test. The tests for spatial lag and spatial error are both not significant, pointing that spatial Durbin can be further simplified. The less significant test is the one for spatial error leading us to choose this one as the best model. The choice has to be done not only on the basis of the statistical tests but also in relation to the context and the previous literature. In this extent, we know that: i) it is highly possible that the absolute beta convergence model is misspecified, ii) Fingleton and López-Bazo (2006) point that authors that use absolute beta convergence models tend to prefer spatial error regressions, iii) Ecuador is not a homogeneous country, so global spillovers are not highly probable.

Table 4 - General-to-specific approach

| **Test** | |
|---|---|
| LR lag | 1.328 (0.249) |
| Wald lag | 1.341 (0.247) |
| LR error | 0.411 (0.521) |
| Wald error | 0.402 (0.526) |
| LR SLX | 9.441 (< 0.01) |

In brackets p-values.

**Source**: authors' elaboration on the basis of INEC.

The results of the spatial regression models are in table 5. Both the coefficients related to the spatial dependence are significant and around 0.025. The speed of convergence is 2.77% in the case of spatial error model and 2.53% for the spatial lag model. The comparison of the AIC with the OLS estimation shows that there has been a gain of efficiency in using spatial models, but the strongly significant presence of heteroskedasticity in the residuals points that misspecification problem is still present.

Table 5 - Spatial models estimates

| **Variable** | **Spatial error** | **Spatial lag** |
|---|---|---|
| Constant | 0.179 (0.067) *** | 0.179 (0.067) *** |
| log(GVA/person) | -0.026 (0.009) *** | -0.024 (0.008) *** |
| λ | 0.253 (0.080) *** | |
| ρ | | 0.238 (0.080) *** |
| AIC | -588.450 | -587.410 |
| Wald test (p-value) | 3.16 (< 0.01) | 8.936 (< 0.01) |
| Breush Pagan test (p-value) | 8.974 (< 0.01) | 7.835 (< 0.01) |

*Significant at 1%, ** significant at 5%, *** significant at 10%. In brackets p-values.

**Source**: authors' elaboration on the basis of INEC.

The results related to the rate of absolute convergence found in this study are comparable with some recent contributions summarised in table 6. Previous studies refer mainly to provincial level, finding that convergence has been around 2.70% during the nineties. Then, there has been a reduction with values between 0.56% and 1.74% for period 2001-2007, associated to the series of economic crisis of 1999. The absolute convergence rate found by Mendieta (2015b) for period 2007- 2012, is around 1.83% for provinces, and 1.37% for cantons, lower than the 2.77% found in this study.

Table 6 – Reported convergence speed in some recent studies about Ecuador

| Study | Variable | Method | Periods | Absolute β |
|---|---|---|---|---|
| | | PROVINCIAL LEVEL | | |
| Ramón, 2009 | GVA per capita (no oil) | Cross-section | 1993 - 2000 | 1.22% |
| | | Linear OLS | 2001 - 2007 | 0.58% |
| Valdivieso, 2013 | GVA per capita (no oil) | Cross-section | 1993 - 2000 | 0.56% |
| | | Linear OLS | 2001 - 2012 | 1.84% |
| Mendieta, 2015a | GVA per capita | Cross-section | 1994 - 1999 | 2.70% |
| | (no provinces producing oil) | Non-linear least squares | 2001 - 2006 | 1.74% |
| | | | 2007 - 2012 | 1.83% |
| | | CANTONAL LEVEL | | |
| Mendieta, 2015b | GVA per capita (no cantones producing oil) | Cross-section | 2007 - 2012 | 1.37% |

**Source**: authors' elaboration on the basis of INEC.

These results suggest a process of absolute convergence at subnational level in Ecuador. Anyway, the question to which these studies do not answer is if convergence is present across the whole country. Or, in other terms, if convergence is something that characterises all cantons or only some groups (clubs).

The possibility of differentiated convergence clubs can be accounted using the Moran scatterplot in order to determine the cluster of cantons that show similar initial conditions in the fashion of Ertur et al. (2006). In this extent, each quadrant is recognised as a convergence club because Moran scatterplot illustrates the complex interrelations between global spatial autocorrelation and spatial heterogeneity in the form of spatial regimes.

The regression analysis in table 7 shows that the spatial autocorrelation is absent (quadrants 2 and 4) or very low (quadrants 1 and 3) and spatial regression analysis is not required according to LM tests. Only in quadrant 1 and 3, high-high and low-low, respectively, we have significant convergence rates. The first club converge at 6.22% rate, and the third at 5.73%. This is not a negligible result for at least two order of reasons. The first concerns the fact that the cluster of more developed cantons in converging at a higher rate than the less developed, and the second is that 75 out of 214, the 35% is not converging opening a problem of sustainability of economic growth in the long-run within the country.

Table 7 - Spatial models

| Variable | Quadrant 1 | Quadrant 2 | Quadrant 3 | Quadrant 4 |
|---|---|---|---|---|
| Constant | 0.404 (0.195) ** | 0.021 (0.337) | 0.231 (0.193) * | -0.987 (0.222) |
| log(GVA/person) | -0.054 (0.024) ** | -0.003 (0.046) | -0.050 (0.027) * | 0.009 (0.038) |
| AIC | -141.480 | -111.179 | -242.084 | -82.873 |
| $R^2$ (adj,) | 0.082 (0.065) | 9.7e-05 (-0.028) | 0.042 (0.030) | 0.003 (-0.025) |
| F-test (p-value) | 4.922 (0.031) | 0.003 (0.953) | 3.545 (0.063) | 0.115 (0.736) |
| Moran's I on residuals (p-value) | 0.201 (0.040) | -0.050 (0.525) | 0.142 (0.055) | 0.228 (0.102) |
| Breush Pagan test (p-value) | 0.494 (0.482) | 2.417 (0.120) | 2.196 (0.138) | 0.084 (0.772) |
| LM error | 2.333 (0.127) | 0.066 (0.798) | 2.032 (0.154) | 1.264 (0.261) |
| LM lag | 1.550 (0.213) | 0.066 (0.797) | 2.393 (0.122) | 1.365 (0.243) |
| Robust LM error | 2.020 (0.155) | 0.060 (0.806) | 0786 (0.375) | 2.301 (0.129) |
| Robust LM lag | 1.236 (0.266) | 0.061 (0.805) | 1.146 (0284) | 2.402 (0.121) |
| LM SARMA | 3.569 (0.168) | 0.127 (0.938) | 3.178 (0.204) | 3.666 (0.160) |
| Number of cantons | 57 | 38 | 82 | 37 |

*Significant at 1%, ** significant at 5%, *** significant at 10%. Standard error in brackets. In brackets p-values.

**Source**: authors' elaboration on the basis of INEC.

## 5. Conclusions

The analysis overviews the theoretical and the empirical motivation for the inclusion of the spatial dimension in growth analysis at subnational level. The theoretical justification is mainly due to the possible knowledge spillovers caused by proximity in space, supported also from the empirical literature that finds that spatial autocorrelation matters for convergence. The results highlight that the spatial autocorrelation across Ecuadorian cantons is not very high but significant. The spatial distribution of Gross Value Added in 2007 and 2012 is quite persistent and heterogeneous. The average growth was also not widespread in space and, often, the cantons that growth at higher rates are located close to others already developed. The regression analysis shows that absolute convergence process is present and the convergence rate is a little bit higher than the correspondent OLS estimation. The results, in any case, have to be refined by adding further explanatory variables because the chosen spatial error model might point to misspecification problems. The identification of convergence clubs through the Moran scatterplot allows the estimation of a single equation for each club. Convergence regards the clusters of most developed and less developed cantons, respectively, while the others are not able to converge opening various policy implications related to i) the capacity of cantons to take advantage from the positive dynamics of neighbours, ii) the persistence of development paths in some circumscribed areas, and iii) the spatial unbalanced development. These problems are very important if we consider that 35% of cantons do not converge and that this could inhibit the balanced growth in a country already characterised by persistent geographical dissimilarities and increasing territorial inequality.

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Appendix A - cantons per quadrant

| Quadrant 1 | | | Quadrant 2 | | |
|---|---|---|---|---|---|
| Canton | GVA per capita 2007 | GVA per capita 2012 | Canton | GVA per capita 2007 | GVA per capita 2012 |
| Chambo | 1939.3 | 1574.74 | Archidona | 986.26 | 1252.55 |
| Chilla | 1939.46 | 1586.11 | Sigchos | 1032.79 | 728.21 |
| Zaruma | 1995.83 | 2068.88 | Muisne | 1077.86 | 1159.73 |
| Giron | 2000.05 | 1237.65 | Rocafuerte | 1136.57 | 795.11 |
| Echeandia | 2007.31 | 1525.37 | Palora | 1156.72 | 1476.8 |
| Atacames | 2025.88 | 2306.9 | Rioverde | 1160.85 | 1414.25 |
| Huaquillas | 2036.7 | 2045.99 | Jaramijo | 1169.81 | 2442.92 |
| Patate | 2055.84 | 1260.74 | Camilo Ponce E. | 1201.63 | 851.89 |
| Piṇas | 2059.07 | 2286.36 | Saraguro | 1249.93 | 1253.39 |
| Chaguarpamba | 2061.61 | 1627.64 | Pimampiro | 1317.74 | 1029.11 |
| San Jacinto | 2068.72 | 1527.86 | Pucara | 1345.93 | 827.13 |
| Salcedo | 2093.39 | 2098.77 | Caṇar | 1395.52 | 1389.95 |
| San Pedro De P | 2111.51 | 1795.84 | Tisaleo | 1421.29 | 990.06 |
| Pasaje | 2111.92 | 2164.5 | Cascales | 1453.82 | 1507.14 |
| Samborondon | 2180.62 | 4901.32 | Deleg | 1464.53 | 1648.47 |
| Buena Fe | 2256.6 | 2109.35 | Biblian | 1474.34 | 1867.69 |
| Santo Domingo | 2281.88 | 2711.19 | Daule | 1504.94 | 2106.15 |
| Catamayo | 2294.3 | 1762.18 | Gnral A. Elizalde | 1535.33 | 1727.88 |
| Arenillas | 2355.96 | 2080.94 | Cotacachi | 1592.59 | 1894.96 |
| San Fernando | 2422.83 | 1693.49 | Playas | 1620.34 | 1503.09 |
| Antonio Ante | 2423.27 | 1934.35 | Arajuno | 1624.09 | 1844.42 |
| Santiago de P. | 2437.02 | 1631.68 | Las Lajas | 1631.03 | 1329.34 |
| Atahualpa | 2446.18 | 1245.55 | Mera | 1633.38 | 1528.08 |
| La Concordia | 2454.19 | 2226.67 | Alfredo B. M. | 1649.88 | 1222.49 |
| Carlos Julio A.T | 2459.22 | 1678.51 | Cumanda | 1650.75 | 1566.16 |
| San Miguel B. | 2492.01 | 1824.2 | Loreto | 1667.21 | 1799.89 |
| Quevedo | 2551.28 | 2873.43 | Urdaneta | 1680.09 | 1865.42 |
| Duran | 2565.64 | 3000.76 | El Chaco | 1686.06 | 2016.62 |
| Ibarra | 2566.95 | 3805.33 | Naranjito | 1694.66 | 1414.39 |
| Balsas | 2650.95 | 2581.78 | Penipe | 1695.24 | 1630.55 |
| Paute | 2747.26 | 2252.48 | Caluma | 1815.02 | 1718.32 |
| El Triunfo | 2773.09 | 2545.15 | Santa Clara | 1836.51 | 3101.65 |
| Machala | 2832 | 4414.48 | Pedro Vicente M. | 1866.52 | 1571.93 |
| Pedro Moncayo | 2990.6 | 4617.68 | Otavalo | 1873.89 | 2634.45 |
| El Guabo | 3017.8 | 3558.85 | Espejo | 1877.52 | 2089.85 |
| Portovelo | 3040.7 | 3044.45 | Mira | 1893.48 | 1579.65 |
| Mejia | 3096.32 | 3163.22 | Milagro | 1894.84 | 1819.78 |
| Manta | 3144.23 | 4796 | Gualaceo | 1924.66 | 1389.77 |
| Valencia | 3309.97 | 3314.45 | | | |
| Santa Rosa | 3377.79 | 2827.64 | | | |
| Naranjal | 3415.01 | 2696.63 | | | |
| Guachapala | 3511.81 | 1638.5 | | | |
| Las Naves | 3705.31 | 1366.91 | | | |
| Simon Bolivar | 3776.09 | 2276.9 | | | |
| La Troncal | 3784.08 | 3573.66 | | | |
| Cuenca | 3797.72 | 4613.43 | | | |
| La Libertad | 3886.59 | 2808.38 | | | |
| Rumiðahui | 3902.77 | 5083.75 | | | |
| Tena | 4361.19 | 2202.41 | | | |
| Cayambe | 4430.96 | 3555.98 | | | |
| Quito | 5070.96 | 5746.13 | | | |
| Isabela | 5810.61 | 3391.54 | | | |
| Puerto Quito | 6055.38 | 2262.67 | | | |
| Santa Cruz | 6656.51 | 4866.52 | | | |
| Baṇos de Agua | 7949.22 | 4303.69 | | | |
| San Cristobal | 8438.7 | 6018.61 | | | |

| Quadrant 3 | | | Quadrant 4 | | |
|---|---|---|---|---|---|
| Canton | GVA per capita 2007 | GVA per capita 2012 | Canton | GVA per capita 2007 | GVA per capita 2012 |
| Taisha | 498.94 | 802.68 | Empalme | 1990.68 | 1208.75 |
| Jama | 820.59 | 822.93 | Palestina | 1996.62 | 1487.93 |
| Huamboya | 821.95 | 1039.23 | Olmedo | 2014.49 | 1653.89 |
| 24 De Mayo | 827.88 | 740.19 | San Juan Bosco | 2023.82 | 1933.82 |
| Guamote | 1036.62 | 877.3 | Lomas De Sargentillo | 2027.28 | 884.26 |
| Paquisha | 1043.33 | 1350.74 | Puebloviejo | 2033.22 | 2811.33 |
| Chimbo | 1043.82 | 1272.44 | La Mana | 2040.18 | 1631.61 |
| Chillanes | 1045.95 | 1017.59 | Aguarico | 2088.17 | 1889.62 |
| Espindola | 1052.03 | 1114.12 | Nabon | 2100.59 | 845.1 |
| Santa Ana | 1055.84 | 858.93 | Ventanas | 2138.24 | 2301.3 |
| Pajan | 1066.66 | 926.6 | Bolivar | 2233.38 | 1672.5 |
| Salitre | 1069.29 | 654.3 | Puerto Lopez | 2244.46 | 1359.97 |
| Santa Lucia | 1080.17 | 845.32 | Azogues | 2251.36 | 2912.21 |
| Centinela Del Condor | 1110.23 | 1067.12 | Babahoyo | 2255.07 | 2908.99 |
| Palanda | 1121.17 | 939.43 | Tulcan | 2270.93 | 2938.94 |
| Gualaquiza | 1125.39 | 1597.29 | Portoviejo | 2302.44 | 3007.03 |
| Colta | 1134.71 | 810.09 | Riobamba | 2329.14 | 2970.23 |
| El Pangui | 1160.51 | 1645.96 | Zamora | 2330.55 | 2969.24 |
| Zapotillo | 1169.69 | 1003.02 | San Miguel De Urcuqui | 2365.25 | 1943.62 |
| Nangaritza | 1180.73 | 1399.3 | El Pan | 2491.6 | 1674.68 |
| Chinchipe | 1181.31 | 1200.89 | Quininde | 2561.35 | 3159.02 |
| Vinces | 1220.57 | 1261.81 | Santa Isabel | 2589.12 | 1503.38 |
| Palenque | 1228.88 | 1487.96 | Loja | 2633.34 | 3598.72 |
| Tiwintza | 1233.04 | 1008.69 | Latacunga | 2701.48 | 3895.83 |
| Pichincha | 1236.8 | 863.17 | Montalvo | 2730.38 | 1970.53 |
| Colimes | 1239.72 | 1272.23 | Salinas | 2746.66 | 2798.05 |
| Pedro Carbo | 1240.08 | 896.45 | Pablo Sexto | 2881.04 | 1773.93 |
| Calvas | 1260.65 | 1194.79 | Ambato | 2905.36 | 3782.41 |
| San Miguel | 1261.05 | 1070.71 | Marcabeli | 3515.96 | 1547.53 |
| San Lorenzo | 1263.47 | 1032.02 | Quijos | 3899.67 | 3076.75 |
| Gonzalo Pizarro | 1277.26 | 1558.89 | Balao | 4289.51 | 3179.35 |
| Chone | 1289.31 | 1268.2 | Guayaquil | 4404.46 | 4794.36 |
| Santa Elena | 1294.91 | 2480.47 | Junin | 5149.61 | 5352.78 |
| Eloy Alfaro | 1303.24 | 1332.23 | Esmeraldas | 5272.77 | 3072.65 |
| Pedernales | 1319.7 | 1457.31 | Pastaza | 7536.87 | 10663.7 |
| Yacuambi | 1322.19 | 1191.64 | Crnel. Marcelino Maridueņa | 9910.76 | 12691.62 |
| Santiago | 1328.53 | 1835.44 | Lago Agrio | 11324.79 | 7590.7 |
| Olmedo | 1335.96 | 892.55 | | | |
| Paltas | 1359.22 | 1236.52 | | | |
| Flavio Alfaro | 1361.37 | 1146.21 | | | |
| Suscal | 1368.8 | 1570.28 | | | |
| Quero | 1385.72 | 876.14 | | | |
| Balzar | 1401.33 | 1359.48 | | | |
| Alausi | 1410.29 | 895.99 | | | |
| Jipijapa | 1418.2 | 1118.86 | | | |
| El Carmen | 1427.41 | 1243.88 | | | |
| Limon Indanza | 1430.36 | 1752.71 | | | |
| Sozoranga | 1456.7 | 1118.8 | | | |
| Gonzanama | 1475.6 | 1545.74 | | | |
| Saquisili | 1492.17 | 1041.22 | | | |
| Yantzaza | 1507.28 | 1990.57 | | | |
| Nobol | 1509.57 | 1040.84 | | | |
| Logroðo | 1509.61 | 1631.14 | | | |
| Mocache | 1510.63 | 2453.38 | | | |

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|---|---|---|
| Isidro Ayora | 1518.96 | 1439.67 |
| San Vicente | 1534.34 | 1293.19 |
| Puyango | 1548.15 | 1345.74 |
| Mocha | 1553.34 | 1049.82 |
| El Tambo | 1558.52 | 2673.08 |
| Chunchi | 1573.25 | 1542.24 |
| Sucua | 1573.62 | 1775.16 |
| Pujili | 1579.42 | 1102.5 |
| Pangua | 1597.86 | 1206.47 |
| Pallatanga | 1603.84 | 850.07 |
| Bolivar | 1610.77 | 1367.91 |
| San Pedro De Huaca | 1616.81 | 1808.27 |
| Guano | 1625.91 | 1181.33 |
| Guaranda | 1626.46 | 1941.17 |
| Chordeleg | 1637.67 | 952.62 |
| Macara | 1663.46 | 1780.6 |
| Sucumbios | 1669.99 | 1476.46 |
| Montufar | 1706.35 | 1857.55 |
| Celica | 1720.18 | 1189.93 |
| Tosagua | 1759.97 | 1925.16 |
| Pindal | 1763.33 | 1031.13 |
| Cevallos | 1807.3 | 2002.9 |
| Baba | 1808.19 | 2095.41 |
| Sigsig | 1819.64 | 981.25 |
| Sucre | 1839.96 | 1775.27 |
| Quilanga | 1842.38 | 2324.91 |
| Oṇa | 1873.28 | 1268.01 |
| Morona | 1921.44 | 2531.28 |

**Source**: authors' elaboration on the basis of INEC.