4. ANALYZING THE REGIONAL ECONOMIC CONVERGENCE IN ECUADOR. INSIGHTS FROM PARAMETRIC AND NONPARAMETRIC MODELS

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Abstract

This paper analyses the process of regional economic convergence in Ecuador from 2007 to 2014, using parametric and non-parametric models. Applying a broad range of methods allows deriving complex empirical findings about the process of convergence, in the context of the high economic heterogeneity that persists over time in the Ecuadorian economy. Encouraging the enlargement of private sector, entering and staying more years in education, increasing the effectiveness of public investment and discouraging the inefficient credit activity are found to be important drivers of economic growth and regional convergence. Additionally, the non-parametric analysis reveals that the progress on the path of regional convergence is mainly due to the 2007-2010 upward transition of the group of poorest provinces. Still, the regional GVA distribution remains polarized and it seems that the group of rich provinces advances faster than the majorities' one, making the achievement of regional convergence even more difficult in the years to come.

Keywords: regional convergence, gross value added, parametric models, nonparametric models

JEL Classification: O47, O54.

I. Introduction

Regional disparities in economic growth and economic development are more evident in Latin America than in many other world regions. Little progress has been made over time, so that the regional disparities and economic concentration are still very high in

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these countries. Despite the temporary high growth rates of some countries or regions, the economic and social gaps remain stable over decades (Cuadrado-Roura and Gonzalez-Catalan, 2013). Ecuador shares the same pattern in terms of regional development. But Ecuador's large economic and social heterogeneity at the regional level is not of a great interest only for the "regional" authorities, but also for the national ones, because it could hamper the national economic growth. Analyzing the process of regional economic convergence is therefore strongly required as a first step in formulating and addressing effective economic and social policies to target the regional discrepancies.

This paper aims to analyze the process of regional economic convergence in Ecuador, using data collected for provinces and cantons, data which run from 2007 to 2014. Both parametric and non-parametric models are applied, to allow deriving complex and robust insights about the stage of regional economic convergence in Ecuador.

The novelty of our paper is twofold. First, it identifies a set of policy measures that could enhance regional economic growth and convergence in Ecuador. Second, by complementing the parametric analysis with non-parametric models, it explains for the first time in the literature how the process of regional convergence continues to co-exist together with a large economic regional heterogeneity.

The paper is structured in fifth sections. The first section is the Introduction, the second section revises the literature, the third section presents the data and methodology, the fourth section is the empirical analysis, while the fifth section formulates conclusions and policy recommendations.

II. Literature overview

After the seminal research contribution of Solow (1956), the literature of convergence has continuously developed with new conceptual approaches and methodologies, but the neoclassical growth theory continues to represent the main approach to the study of economic convergence. Although the area of theoretical and empirical contributions to the literature of economic convergence is very broad, only some important steps into its development are highlighted below.

The neoclassical growth theory is based on the assumption that the marginal returns on capital accumulation decrease over time, which allows countries with higher initial capital stocks to growth faster and to reach at some point in the future countries with higher initial capital stocks. This process is called beta-convergence and describes in fact the real convergence toward similar per capita income levels. Under the beta-convergence approach, two hypotheses are generally used to test the process of convergence. The absolute (unconditional) convergence hypothesis states that the per capita GDP of countries/ regions converge regardless of their initial conditions. When controlling for country-specific characteristics, the hypothesis of convergence is called relative (conditional) convergence. Under this hypothesis, two countries/ regions converge to the same steady state level of capital and output per capita only when they have the same economic structure (e.g. education attainments, technological progress, trade openness, factor productivity etc). In the absence of similar conditions, economies will reach their own unique equilibrium.

In the literature of economic convergence, Baumol is considered to be one of the most influential authors who contributed to the empirical validation of the absolute convergence approach. Over time he has developed a series of empirical analyses to test the validity of the absolute convergence approach. Initially he found a negative relationship between the initial level of per capita income and its subsequent growth, which was in fact one of the first and most "cited" validations of the absolute convergence theory (1986). By examining the role of institutional differences in the process of economic convergence, Abramovitz (1986) succeeded to bring another fundamental contribution to the development of conditional convergence approach.

After the significant contributions of Baumol and Abramovitz, the empirical papers of Mankiew, Romer and Weil (1992) and Barro and Sala-i-Martin (1992) notably enriched the literature of economic convergence. Their works have opened a new direction of research focused on measuring the extent of beta convergence in different contexts, as well as on developing new methods to better capture the peculiarities of the complex convergence process. Initially the cross-sectional methods represented the only approach used in the analysis of economic convergence. Later on, panel data methods began to be used as a better methodological technique able to also capture the dynamics of data and processes. In fact, this technique emerged together with the availability of panel datasets and with the progress of computational methods. In the framework of the panel data analysis, a new body of literature oriented toward estimating country-specific effects in the real convergence process was opened with Islam (1995).

In literature, most papers studying the process of economic convergence rely on the neoclassical theory of economic growth which states that countries or regions having lower initial levels of per capita GDP will advance faster than countries which are initially richer. As a response to the increasing empirical evidence of convergence clubs and divergence patterns all over the world, but especially in the European Union, the methodological approaches have slightly moved from the parametric models to the non-parametric ones. However, the parametric frameworks still remains the main approach used to analyze economic convergence. This is because the output from linear models is easier to interpret and allows better assessing the impact of different policy measures.

Most empirical papers studying the economic convergence run cross-country models using data aggregated at the country level. When moving the analysis at the regional level, the same models are used, but generally the rate of convergence is found to be higher. For instance, Ralhan and Dayanandan (2005) apply the first difference Generalized Method of Moments (GMM) model to a panel dataset of 10 Canadian provinces running from 1981 to 2001 and estimate a speed of convergence of 6%. Using the system GMM, Badinger *et al*. (2004) find a speed of convergence of 6.9% across 196 European NUTS2 regions from 1985 to 1999.

Compared to other regions in the world, the literature on regional economic convergence in the Latin America is rather scarce. When using long time periods, most studies focusing on Latin America countries or regions found evidence of convergence. For instance, Serra *et al*. (2006) finds that the regions of six middle-income Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico, and Peru) converged at very low rates over the last three decades. Evidence of convergence is also found

among the Mexican regions from 1940 to 1995 (Esquivel, 1999), and from 1940 to 2009 (Gomez-Zaldivar and Venetosa-Santaularia, 2012), as well as among the Brasilian regions from 1950 to 1989 (Cardenas and Ponton, 1995).

Most papers studying the process of economic convergence in the Latin America use parametric models, and only to a lesser extent non-parametric methods. Among the papers using non-parametric techniques, Canarella and Pollard (2006) discuss about the Latin America's "twin peaks" polarization, revealed when using the intra distribution dynamics approach. Royuela and Garcia (2015) apply parametric and non-parametric techniques to regional data in Colombia running from 1975 to 2005, and find no evidence of economic convergence in terms of GDP per capita.

The analysis of regional economic convergence in Ecuador has been conditioned on the canton and province- gross value added (GVA) availability (running only since 2007 onwards). Using the non-linear least squares method applied to cantonal panel data running from 2007 to 2012, Mendieta Muñoz (2015a) finds an absolute convergence rate of 1.37% and a rate of conditional convergence of 1.12%. These rates are considered by the author too low as to enhance the reduction of regional economic heterogeneity in Ecuador. When further accounting for spatial spillovers, the analysis still reveals the state of convergence at the cantonal level, but also identifies several convergence clubs emerging into the GVA density distribution (Mendieta Muñoz and Pontarollo, 2015b). Ramón-Mendieta *et al.* (2013) also concludes about the existence of a regional economic process in Ecuador, based on provincial data from 1993 to 2011.

III. Methods

In this paper, the process of regional economic convergence in Ecuador is analyzed using parametric as well as non-parametric models. As explained in Introduction, using two different methodological frameworks instead of a single one allows deriving more and complex empirical insights about the process of regional convergence, in the context of the high economic regional heterogeneity. The first section of our empirical analysis examines the unconditional and conditional regional convergence by applying cross-sectional and panel data regression models, while in the second part, the *kernel distribution*, *dip statistic* and *stochastic kernel* are introduced as non-parametric techniques.

The unconditional convergence is analyzed using both cross-sectional and panel regression models, while the conditional convergence is examined just with panel data regression models. In the cross-sectional beta regression model, the growth of per capita GDP in the period of analysis is regressed upon the initial level of per capita GDP growth, using the Ordinary Least Squares (OLS) estimator:

$$\frac{1}{T}\ln\left(\frac{y_{iT}}{y_{i0}}\right) = \alpha + \beta\ln(y_{i0}) + u_i$$

(1)

where: T is the time period; y_{iT} is the GDP per capita at the end of period, y_{i0} is the initial GDP per capita , and u_i is the error term.

In comparison with the cross-sectional approach, the panel models provide several advantages. For instance, the cross-sectional approach doesn't allow capturing the dynamics of the convergence process (Quah, 1997). Also, the country effects in the panel approach allow considering the technological differences among countries/regions[3]. Moreover, there are studies highlighting that the cross-sectional regressions could lead to biased results (Knight *et al*, 1993; Canova and Marcet, 1995; Islam, 1995). One explanation is that the technological and aggregate productivity differences across countries are found to explain the largest part of income differences among countries (Hall and Jones, 1999).

When using panel data, the following panel regression model is generally estimated:

$$y_{it} = \beta y_{i,t-1} + \delta Z_{it} + \eta_i + u_t + v_{it} \qquad (2)$$

where: v_t is the unobserved time-invariant country-specific effect; y_{it} is the logarithm of per capita GDP n region/ country i at time t; Z_{it} is a vector of explanatory variables; β and δ are the parameters to be estimated; η_i is the unobserved country/region specific effects and u_{it} is the standard error term.

Eq. (2) has the following characteristics: $E(\eta_i) = E(u_{it}) = E(v_i\, u_{it}) = 0$ and $E(u_{it}\, u_{js}) = 0$ for $i \neq j$ and $s \neq t$. The most popular estimators used to derive the regression parameters in eq.2 are the Least Squares Dummy Variable (LSDV) or Fixed effects (FE), and the Random effects (RE) or error-components model[4].

Over time, a large set of estimators have been developed to estimate growth regressions, such as: the pooled OLS, Generalized Least Squares (GLS), Minimum Distance (MD), Least Squares with Dummy Variables (LSDV), Arellando and Bond GMM, unconditional maxim likelihood etc. The random effect estimator (RE) is often referred to as being inappropriate to be used in growth regressions because it contradicts the correlation of the country effects with the included explanatory variables (Islam, 2003). This further makes inappropriate the use of RE- GLS in the estimation of growth regressions. Monte Carlo studies are often used to reveal small sample bias.

When the data are affected by endogeneity, heteroskedasticity or serial correlation, alternative estimators should be considered. For instance, when the endogeneity is confirmed, only instrumental variable regressions (e.g. Two-Stages Least Squares, 2SLS and the GMM) or the Heckman selection correction can be used because, in this situation, the regression coefficients in the OLS regression would be biased. Other problems that might arise are the time invariant-country characteristics which could be correlated with the explanatory variables, and the short time-dimension of the panel dataset (or simply the *small* sample).

When only the endogeneity and the fixed-effects problems are found, they could be addressed by using the 2SLS estimator. When the endogeneity is not an issue for the dataset, the GLS is the BLUE estimator. But when both the heteroskedasticity and endogeneity affect the working data, then 2SLS as well as the OLS are not

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[3] The cross-sectional approach assumes identical technologies across countries.
[4] The equations of the FE and RE estimators are very close. The only difference is that the FE equation does not explicitly include the time-invariant observed variables and their coefficient.

asymptotically effi   cient. In this case, the GMM estimator is preferred because it is more efficient. This is even more desirable when the serial correlation is also found (as it is in most panel datasets).

Estimating eq. (2) by the GMM estimator (i.e. the first difference- and system GMM) involves two steps. The first step is to difference the regression equation to eliminate the country spec   ific effect η_i and therefore to avoid omitted variable bias. Using values of Z_{it-s} in levels (z>1) as instruments for ΔZ_{it} is probably correlated to the differenced error term.

$$\Delta y_{it} = \alpha_t - \alpha_{t-1} + \beta \Delta y_{it-1} + \Delta \delta Z_{it} + \Delta u_{it} \qquad (3)$$

Second, a set of assumptions should be assumed: (a) the instruments Z_{it-s} (s ≥ 2) are not correlated with current or past errors, and therefore not correlated with Δu_{it}; and (b) there is no serial   correlation in the error term.

The Arellano an d Bond (1991) two-step "GMM difference" estimator can be derived from the following moment conditions:

$$E[Z_{it-s} \Delta u_{it}] = 0 \text{ for } s \geq 2 \text{ and } t = 3,..., T. \qquad (4)$$

The system GMM is finally obtained by adding the original equation in levels to the equation in differe   nces (Arellano and Bover, 1995). This leads to more efficient estimates because it uses additional instruments. In fact, the variables in levels are instrumented by their first differences when assuming that the latter are not correlated with the unobserved country effects.

After discussing the estimation methods that will be used in the empirical section, we come back to the signification of the β coefficient in eqs. (1) and (2). A negative and significant value of β indicates the process of convergence. In eq. (2), when restricting the value of δ to 0, the model presented gives insights to the process of absolute convergen   ce (e.g. Yin et al., 2003, Geppert *et al*., 2005), while it is freely estimated the output gives insights to the process of conditional convergence (e.g. Neven and Gouyette, 1995, Cappelen *et al*., 2003).

Beside the coefficients generated by the *beta* regression models, other indicators of convergence could be also derived: the *speed of convergence* and *half-life of convergence*. The speed of convergence is in fact the speed of converging to the steady-state, while the half-life of convergence is defined as the time necessary for economies to cover half of the initial lag from their steady state. The literature usually reports speed rates of ar   ound 2% which implies a half life of 28 years. This has often been referred to as the "iron low of convergence", a natural constant or statistical artefact (Barro and Sala-i-Martin, 1992; Abreu *et al*., 2005).

The speed of convergence is calculated upon the formula: $s = -ln(1+ \beta) /T$, where T denotes the tim e span of the convergence analysis. The half-time convergence can be derived from the half-time equation:

$$[1-exp(-\beta T)] = 0.5 \qquad (5)$$

where: T denotes the number of years required to close half of the gap at a given rate of convergence.

Recently, a new indicator has been proposed to measure the pace of catching-up more developed regions (Halmai and Vasary, 2010). Despite the negative sign that characterises both processes, the catch-up rate and convergence rate are different. The beta convergence shows the pace of progress, while the catch-up rate indicates the distance to be achieved toward convergence.

$$\text{Catch-up rate} = 100 \frac{\Delta(y_{it} - y_t^*)}{(y_{it-1} - y_{t-1}^*)} \tag{6}$$

where: y_{it} is the level of per capita GDP for country *i* at time *t*, y_t^* is the national or regional average value of y_t , and *Δ* is the variation between *t* and *t-1*.

In the second part of the empirical section non-parametric methods are also used, as to reveal new aspects of regional convergence in Ecuador. The Kernel density estimation and the stochastic kernel density are used here.

The first step of the non-parametric analysis consists of calculating the *dip* statistic in order to assess the (multi)modality of income distribution. Hartigen J.A. and Hartigen P.M. (Hartigen and Hartigen, 1985) are the authors of the *dip* statistic which calculates the maximum difference between the empirical distribution function (F) and the unimodal distribution function (F_n) that minimizes that maximum difference. With the *dip* statistic it is possible to detect whether the income distribution is unimodal or not.

$$dip \equiv \min_{F \text{ uni mod } al} \ \max_x \left| F(x) - F_n(x) \right| \tag{7}$$

The kernel function allows studying the distribution of GVA per capita in Ecuador's provinces by probability density functions. With the kernel density estimators, the representation based on histograms which are not smooth, and which depend on the width of the bins and the end points of the bins, is considerably improved by the cantering of a kernel function at each data point (Raileanu-Szeles and Albu, 2015). A brief presentation of the kernel methodology used in the empirical section, is based on the main methodological steps also followed by Laurini *et al* (2005) and Li and Racine (2007):

A kernel can be defined as a continuous, limited and symmetric function, whose indefinite integral is equal to unity.

$$\int K(u)d(u) = 1 \tag{8}$$

where: *K* is the chosen kernel function. The density estimator can be represented as the density function for the scalar Z at the point z_0:

$$f(z_0) = \lim_{h->0} \frac{1}{2h} P(z \in (z_0 - h, z_0 + h)) \tag{9}$$

The estimator for the $\hat{f}(z_0, z)$ could be of the following form:

$$\hat{f}(z_0, z) = \frac{\#(z \in (z_0 - h, z_0 + h))}{2hn} \tag{10}$$

Based on (9) and (10), the kernel density estimation can be written as:

$$\hat{f}(z_0, z) = \frac{1}{nh} \sum_{i=1}^{n} K(\frac{z_0 - z_i}{h}) \tag{11}$$

The kernel function used in (5) includes the indicator function I and takes this form:

$$K(u) = \frac{1}{2} I_{(-1,1)}(u) \tag{12}$$

The Gaussian kernel, which is selected to be used in the empirical section, could be defined as follows:

$$2\pi^{-1/2} \exp(-u^2) \tag{13}$$

The parameter *h* in equations (9)-(11) is the bandwidth parameter and it is used to control the degree of smoothing, by attributing weighting to the points $z_i \neq z_0$.

In the last part of the non-parametric analysis, the stochastic kernel density function of the GVA per capita distribution is analyzed. This transition probability function gives insights to the functional relationship of the transitions between different states, according to a certain probability distribution. The stochastic kernel indicates how the probability distribution changes over time, being a summary of the first moment, last moment and the transitions during the periods. In comparison with the stochastic kernel, the traditional beta-convergence approach only looks at the transition relative to the first period without looking at the last moment, while the sigma- convergence approach uses only a part of the available information in the data to derive standard deviations for all observed periods (Weber, 2009). This is the main advantage of the stochastic kernel density method over alternative parametric methods.

One of the most important contributions to the literature of distribution dynamics belongs to Quah (1997). He uses the stochastic kernel to examine the incipient polarisation and stratification, as well as emerging of twin peaks. With this new approach he derives new empirical insights that couldn't be revealed with the traditional parametric analysis.

Following the methodology described in Kar et al. (2010), if we assume that the distribution of GDP per capita at time t is φ_t, then the dynamic of distribution can be represented as a first order autoregressive process:

$$\varphi_t = T(\varphi_{t-1}, u_t), \quad t \geq 1 \tag{14}$$

where: u_t is the error term and *T* is the operator describing how one part of the distribution changes into another one, from time *t-1* to time *t*, i.e. is represented in the continuous yield space by the stochastic kernel.

Equation (14) can alternatively be written as:

$$\varphi_t = T_{ut}(\varphi_{t-1}), \quad t \geq 1 \tag{15}$$

where: T is the stochastic kernel which describes the distribution dynamic over time.

By several iterations and considering the Markov chain assumptions, the dynamic of the distribution at time *t+S* is:

$$\varphi_{t+S} = (M^S)' \varphi_t \quad \text{for all } s \geq 1 \tag{16}$$

The ergodic distribution can be represented as a long term distribution and results from iterating the system up to infinity.

$$\varphi_\infty = M' \varphi_\infty \, , \, S \to \infty \tag{17}$$

where: φ_∞ is the ergodic distribution of GDP per capita across countries/ regions and *M* is the transition matrix. If the ergodic distribution *S* is found to be unimodal, then it suggests the convergence process developing over time. The bimodality indicates polarisation, while the multimodality (identification of more than two modes) is an indicator of stratification.

IV. Data presentation and analysis

We use data on per capita Gross Value Added (GVA) for a number of 24 provinces and 221 cantons, over the period 2007-2014. This is the longest available panel dataset on regional GVA per capita in Ecuador. Our data are collected from the large datasets of the Ecuador's Central Bank and national surveys. Beside the GVA, the analysis of conditional regional convergence in Ecuador also requests a set of variables suggestive for the policy measures that could enhance the economic growth and convergence. The variables included into our analysis are: the BNF credits (agricultural credits granted by Banco Nacional de Fomento del Ecuador), population growth, public investment (as % in GVA), education (number of years of schooling) and private sector (percentage of employees working in the private sector).

Before presenting the results of the quantitative analysis, we provide a short descriptive analysis of the GVA dynamic which allows the reader to better understand the process of real economic convergence in Ecuador.

In Fig.1 the GVA in 2007 (the initial year of our time period) is plotted on the horizontal axis against the mean of the GVA growth rates from 2007 to 2013, on the vertical axis. This relationship gives insights to the process of regional convergence in Ecuador, at the cantonal (b) and provincial level (a). Both figures (a) and (b) suggests the existence of important outliers, as well as a high heterogeneity as regards the GVA growth patterns. However, Fig.1b exhibits no pattern of convergence at the cantonal level, while at the provincial level, Fig.1a suggests a slight process of convergence with a high concentration in the area of low initial GVA per capita and high average growth rates (the upper-left corner). A negative relationship between the initial GVA per capita and the average growth rate would be a clear indication of economic convergence.

In Fig.1b most cantons had initial levels of GVA per capita in the same low range of values, but over time they have followed different growth patterns. Only few cantons had high initial GVA levels, but over time they have also embarked on different growth

trajectories. Instead of a reverse relationship which is typical for the convergence process, Fig.1b rather reflects a process of economic divergence.

Convergence patterns at the cantonal and provincial levels, 2007-2013

a) Provincial level (24 provinces)   *b) Cantonal level (221 cantons)*
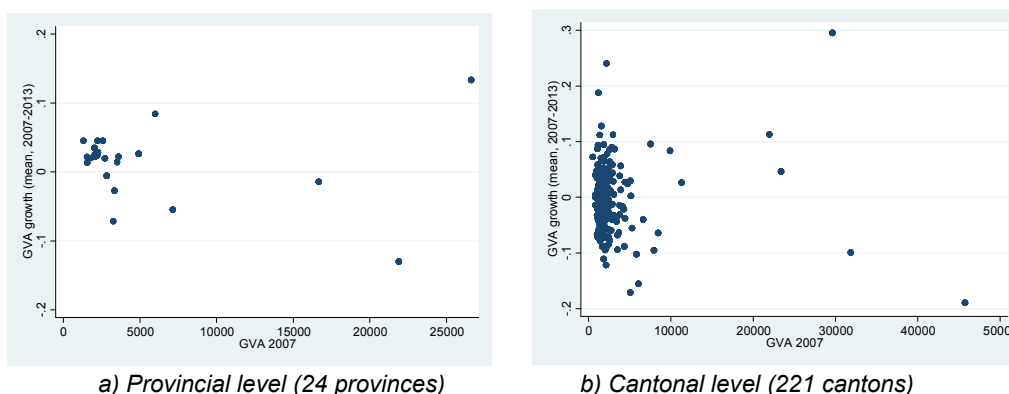
Note. In Fig. 1 (a), Orellana, which is placed in the upper-right corner, can be considered as an outlier. In Fig. 1 (b), the canton La Joya de los Sachas, also being an outlier, is not represented on the chart.

In conclusion, the descriptive analysis briefly presented in this section doesn't reveal any sign of economic convergence at the provincial and cantonal levels.

V. Empirical results and discussion

In this section we apply a set of parametric and non-parametric methods to describe the regional economic convergence in Ecuador, mostly at the provincial level, and to finally conclude about the stage and successfulness of this process.

In the first part, the beta unconditional and conditional convergences are analyzed at the cantonal and provincial level, using both cross-sectional and panel data. Different estimators as well as different sets of explanatory variables are used in the analysis of conditional beta convergence. Second, non-parametric techniques are also introduced to provide additional empirical insights.

Following the standard convergence approach, the unconditional beta convergence is first examined, at the cantonal and provincial levels, using the OLS estimation and cross-sectional data.

According to Table 1, the negative and significant coefficient of the *beta* regression model indicates the achievement of absolute convergence at both the provincial and cantonal level. At the provincial level, the unconditional convergence is found to be deeper than at the cantonal level where the signification of the *beta* coefficient is also weaker.

Table 1

Unconditional beta convergence (Cross-sectional approach)

Variables	Cantonal level	Provincial level[5]
	Coefficients (St.err.)	Coefficients (St.err.)
Beta coefficient	-0.0103** (0.001)	-0.0421*** (0.004)
Constant	0.06*** (0.01)	0.34*** (0.03)
Speed of convergence	1.07%	5%
Half-life convergence	67.29 years	16.46 years
Nr. obs.	221	24

This result is somehow contrasting to the "lack of convergence", which is even more obvious at the cantonal level, as revealed by Figure 1.b. As shown in Table 1, a number of 221 Ecuadorian cantons tend to converge at an annual average speed of around 1.07%. At this speed, using half-life convergence, it will take 67 years to eliminate half the initial gap to the steady state. When moving from cantons to provinces, the half-life convergence significantly decreases to around 16 years and the speed of convergence increases almost 5 times.

The conclusion arising from this simple analysis is that a deeper disaggregation is associated to a lower unconditional convergence, which is suggestive for the high heterogeneity characterising the Ecuadorian regional economy (Mendieta Muñoz, 2015a; Mendieta Muñoz and Pontarollo, 2015b).

Table 2 presents the 7-years average annual rate of catch-up for the 24 Ecuadorian provinces, from 2007 to 2013. The catch-up rate measures the average percentage change in the gap between each province's per capita GDP and the national average.

Table 2

Average catch-up rates, 2007-2013 (%)

Azuay	1.27%	Galapagos	-114%	Orellana	12.58%
Bolivar	-1.28%	Guayas	14%	Pastaza	53%
Cañar	-2.07%	Imbabura	-5%	Pichincha	440.59%
Carchi	-2.42%	Loja	-2.39%	Santa Elena	8.99%
Chimborazo	-2.66%	Los Rios	-2.52%	Santo Domingo	-16.94%
Cotopaxi	-2.16%	Manabi	-3.80%	Sucumbios	2.63%
El Oro	-6.59%	Morona Santiago	-1.33%	Tungurahua	-2.55%
Esmeraldas	12%	Napo	9.26%	Zamora Chinchipe	-1%

A positive catch-up rate suggests that the gap between a province and the national mean is widening, while a negative rate means that the gap is falling. According to the results presented in Table 2, in the process of regional convergence, Galapagos and Santo Domingo are catching-up at a fast pace, while for Pichincha, Pastaza, Guayas and Orellana, the catching-up is found to be very slow. However, the diversity of results

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[5] *Given the very small sample at the provincial level (24 provinces), we are aware that this regression output should be interpreted with prudence. However, these results are provided here especially for comparison purposes.*

shows, once again, the high heterogeneity that characterizes the Ecuadorian regional economy.

The examination of unconditional beta convergence process using a panel data approach is the next step of our analysis. The robustness of beta estimates is assessed by comparing different estimators, i.e. the Fixed-effects (FE) and RE.

The FE approach allows unobserved regional heterogeneity, provides more efficient estimates, presents more variability and less collinearity and usually provides higher *beta* rates (Evans, 1997; Etzo, 2008). The LSDV estimation was first used by Islam (1995) to control for the individual country effects, and is also known as the FE estimator with dummy variables.

Over time, many papers suggest using the FE approach to estimate growth regression models (e.g. Islam, 1995, 2003; Acemoglu *et al*., 2008), because it allows for the permanent unobserved country characteristics which are correlated to the observed GDP per capita. From this point of view using this estimator allows capturing the characteristics of the Ecuador's regional economy. Some provinces are rich here because they have specific characteristics which persist over time (e.g. Guayas, Azuay), while others have their own specific peculiarities which continuously fuel their status of poor Ecuadorian provinces (e.g. Zamora Chinchipe, Morona Santiago). Neglecting these unobserved province- characteristics could result in biasing downward the estimated convergence rate.

But despite the advantages that the FE estimator has over alternative methods, Nerlove (2000), Arellano and Bond (1991) and others underline that when the panel is short or even moderate, the FE is biased downward. This drawback, which is referred to as the *Hurwicz bias*, leads to overestimated convergence rates. This is also reflected by our results which reflect a much higher convergence rate estimated by the FE in comparison with the RE.

Table 3
Unconditional beta convergence (panel data regression models)

Variables	Cantonal level		Provincial level	
	FE	RE	FE	RE
	Coef. (St.err.)	Coef. (St.err.)	Coef. (St.err.)	Coef. (St.er.)
Beta coefficient	-4.34*** (.20)	-0.11* (.07)	-0.48*** (.04)	-0.03** (.01)
Constant	33.09*** (1.51)	-0.89* (.52)	3.93*** (.38)	0.26*** (.13)
Speed of convergence	-	26.11%	569%	3.39%
Half-time	-	6.30 years	1.44 years	23 years
Nr. Obs.	1547	1547	168	168

Note. At the cantonal level, the speed of convergence and half-time are not reported in the FE approach because we suspect that the estimates are highly downward biased.

In line with previous papers (starting with Islam, 1995), our paper indicates a much higher convergence both at the cantonal and provincial levels when using panel data estimation techniques, compared to the OLS. Moreover, a higher *beta* coefficient leads to a higher speed of convergence and a lower half-time convergence for cantons and provinces. According to Nerlove (2000) and Arellano and Bond (1991), and given the very high beta values provided by the FE approach, we suspect that they are biased

downward due to our small sample. When using panel data, the unconditional convergence is found to be deeper at the cantonal level than at the provincial one. However, these results should be interpreted with prudence not only because of the small sample, but also because of the low *beta* significance in the RE model (especially at the cantonal level).

The examination of conditional beta convergence represents the next step of our empirical analysis. As previously discussed, the FE approach provides more efficient estimates and less colinearity because it allows for the permanent unobserved country characteristics which are correlated to the observed per capita GDP. But it is found to produce downward biased estimates when the dataset is small. Moreover, the FE estimator produces even higher small sample bias when estimating the coefficient of time-varying explanatory variables (Arellano and Bond, 1991).

The use of a large set of explanatory variables allows avoiding the FE method, because in this case there is just a small fraction of omitted variables correlated to the GDP per capita. But this approach is difficult to undertake here because of the dataset limits. Moreover, when using the FE estimator, the explanatory variables which don't exhibit a high variation over time within provinces, or those which are time-constant within provinces, either cannot be accurately estimated, or are not found significant. In this context, the use of FE, as well as of RE, is problematic with our data.

As explained in the previous section, to overcome the problems of serial correlation, heterokedasticity and endogeneity, we decide to use only the GMM and 2SLS estimators[6] in the analysis of conditional regional convergence

Two different sets of explanatory variables are successively examined in order to confirm the achievement of conditional convergence. This empirical approach provides robustness to our analysis and reveals more insights about this complex regional process (Tab 4 and Tab 5).

First, the GVA per capita is regressed upon a set of explanatory variables that we initially presume being determinants of economic convergence. For comparison, three estimators are used: the difference- and system GMM, as well as the 2SLS. The variable "private sector" is included into the regression analysis just in models (2), (4) and (6). In both GMM models the only first lag of endogenous variables are used as instruments, with the exception of the variable "investment share", for which the first and the second lag are used. In the 2SLS model the first and second lag are accounted as instruments. Although, in general, deeper lags are better instruments, they would reduce our sample size which however is a small one.

The Arellano-Bond test for AR(1) and AR(2) in first differences, as well as the Sargan test are applied to help building up the models (1)-(4) in Tab 4, and model (7) in Tab.5. The AR(2) test on the residuals in first differences detects autocorrelation in levels variables, being therefore more important than the test for AR(1) process in first differences which usually rejects the null hypothesis. In fact, The Arellano – Bond test for autocorrelation has a null hypothesis of no autocorrelation and is applied to the differenced residuals, while the Sargan test has the null hypothesis of "the instruments

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[6] *The Woolridge test and the likelihood-ratio test (LR test) confirm the presence of serial correlation and heteroskedasticity in our data.*

as a group are exogenous", which makes desirable higher *p*-values of the Sargan statistic.

In Tab.4, as indicated by models (1)-(6), most explanatory variables have a significant effect over the GVA, and they enhance the process of conditional beta convergence. Under all models, the *beta* coefficient of the GVA logarithm is negative, which indicates the achievement of the conditional beta convergence. The *beta* estimates are very close in the system GMM and 2SLS, while the difference GMM estimates much higher *beta* values. However, given our small sample, as often mentioned throughout the paper, the difference GMM should be interpreted with prudence. For both sets of GMM estimates, we use the finite-sample Windmeijer correction in order to avoid the downward bias in the standard errors.

When being significant, the effects of explanatory variables on the GVA are similar under all estimation models, which suggest the consistency of estimates (Tab.4).

The effect of population growth on economic growth is significant and positive (with the exception of the difference- GMM). The population growth in Ecuador is found to enhance economic growth, which is in line with the neoclassical growth model that associates the population growth to the technological advancement. However, there is a large body of literature discussing this particular topic, and the empirical findings are very broad and diverse.

The BNF credits have a significant negative effect on economic growth in all models (1)-(6). The BNF credits are provided by El Banco Nacional de Fomento del Ecuador, which is a public financial institution primarily oriented toward the rural sector and agriculture financing. According to our results, the expansion of BNF credits seems to hamper economic growth and regional convergence, which apparently could be confusing. Its highly significance and constant negative coefficient under all models in Table 4 reveals a specific pattern of the economic structure – the inefficiency of small farms and small agricultural companies, which are not enforced by the BNF credits. Therefore, instead of producing economic growth, this type of credit discourages it. In the light of our empirical results, the BNF credits seem to be inefficient at the macroeconomic level.

The public investment (as % of the total GVA) is also found to have a negative influence on economic growth, but only in the GMM models. According to our result, reducing public investment seems to enhance economic growth. This finding supports a large body of literature arguing that sometimes public investment is inefficient and not able to indirectly boost private investment and economic growth (e.g. Devarajan, Swaroop, and Zou, 1996; Khan, 1996). In the case of Ecuador, the analysis of this variable should be placed in the general macroeconomic framework. The regional economic development in Ecuador is characterised by a large heterogeneity. Some cantons and provinces are far less developed than the others, so that they request more public investment. In Ecuador the public investment policy is managed by two types of public authorities- at the national level and regional level. Given that the regional level- authorities are more able to address the regional disparities, decentralizing even more the public investment policy could be seen as a measure stimulating economic growth.

.Education has only a slightly significant positive effect in our study, under the system GMM and 2SLS models. Encouraging the young generation to spend more years in the educational system could be a policy measure able to generate positive, but not

powerful effects on economic growth. The important role played by the human capital in the process of conditional convergence, especially when the human capital is proxied by the number of schooling years, has also been revealed in European integration studies (Pentecost, 2011). In Ecuador, previous studies have identified the importance of education in stimulating economic growth. For instance, the World Bank (2005) points out that the creation of a considerable mass of secondary educated workers is strongly needed in Ecuador, for enabling participation in more technologically advanced sectors.

The impact of the "private sector" variable is examined just in models (2), (4) and (6). The proportion of total employees working in the private sector is found to be a significant and strong determinant of economic growth under all models. Employing more people in the private sector, compared to the public sector (municipal and fiscal institutions), stimulates economic growth. This is in line with our expectations, as in any free market economy, the private sector is widely recognized as engine of the economic system. Extending the private sector by increasing the proportion of people employed in the private sector exerts a positive effect on economic growth in Ecuador.

Overall, there is clear evidence of conditional convergence in models (1)-(6), and the most powerful determinants are found to be the number of schooling years, population growth and employability in the private sector. Stimulating the school attendance, as well as the private sector enlargement, is particularly important in stimulating economic growth, because they could generate important positive policy implications.

Table 4

Conditional convergence, Ecuadorian provinces

Variables	System GMM		Difference GMM		2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln GVA (Lag 1)	-0.349***	-0.414***	-0.903***	-0.786***	-0.341**	-0.354***
	(0.06)	(0.04)	(0.10)	(0.11)	(0.08)	(0.08)
Population growth (ln)	0.023**	0.016	0.009	0.008	0.025***	0.019**
	(0.01)	(0.01)	(0.007)	(0.008)	(0.01)	(0.009)
BNF credits (ln)	-0.08***	-0.066***	-0.090***	-0.099***	-0.088***	-0.048*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)
Public investment	-0.078*	-0.038	-0.158***	-0.082**	-0.053	-0.072
	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)
Education	0.020*	0.019**	-0.027	-0.019	0.024*	0.027**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.009)	(0.01)
Private sector (ln)	-	0.086***	-	0.105**	-	0.083***
		(0.02)		(0.05)		(0.03)
Constant	2.351***	3.160***	-	-	2.210***	2.689***
	(0.46)	(0.03)			(0.58)	(0.61)

Notes. (1) Dependent variable in models (1)-(6): the growth rate of VAB per capita; (2) *** p<0.01, ** p<0.05, * p<0.1; (3) 2SLS instruments: First and second lag of the variables: private sector, BNF credits and investment share. Difference and system- GMM instruments: ln GVA, investments share and BNF credits; (4) The resulting standard errors are consistent with panel-specific autocorrelation and heteroskedasticity in one-step estimation.

Beside the model whose estimates are reported in Table 4, we have also applied a *human capital augmented Solow* model to check for the robustness of the *beta* estimates and some of the explanatory variables used in models (1)-(6). The human capital augmented Solow model fits the general panel regression model presented in eq. (2), but can also be specifically written as follows:

$$\Delta y_{it} = \alpha_0 + \alpha_1 y_{it-1} + \alpha_2 \ln(h_{it}) + \alpha_3 \ln(s_{it}) + \alpha_4 \ln(n_{it} + g + \delta) + \eta_i + v_{it} \qquad (18)$$

where: *s* is the savings (investments) rate, *h* is the human capital, *n* is the population growth rate, *g* is the labour-augmenting technological progress, *δ* is the rate of the physical capital depreciation. All parameters follow the general panel data regression framework as described in the methodological section.

When analyzing the process of conditional convergence in Tab.5 by an augmented Solow model, we have to adapt some variables of interest to this specific model. The human capital is measured by the number of schooling years, as in models (1)-(6), but the investment rate is proxied this time by the public investment per capita. We follow previous papers and assume that the sum *g+δ* is constant at 0.05 (e.g. Mankiev *et al.*, 1992).

Beside the system GMM and 2SLS models, the RE estimates are also reported in Tab.5. This is because the RE could be used as a "bounds test of small sample biases" (Brülhart and Mathys, 2008). The difference GMM estimates are not reported for two reasons: (1) The *beta* are generally found to be much higher in the difference GMM, as also shown in Table 4; (2) The system GMM has a lower bias and higher efficiency under small samples (Soto, 2009).

The results confirm the findings revealed by models (1) - (6) in Table 4. The negative and significant *beta* coefficients suggest once again the achievement of the conditional beta convergence at the provincial level in Ecuador. Education and reformulation of public investment policy (in terms of effectiveness and decentralisation) have significant and positive effects on economic growth, being in the same time powerful drivers of conditional regional convergence in Ecuador. This secondary set of empirical findings confirms and strengthens the results reported in Table 4.

Table 5

Conditional convergence (Ecuadorian provinces)

Variables	System GMM (model7)	Random effects (model 8)	2SLS (model 9)
Ln GVA (Lag 1)	-0.1146*** (0.04)	-0.11*** (0.03)	-0.1278* (0.07)
Public investment	-0.0306* (0.01)	-0.03*** (0.01)	-0.0490** (0.02)
$\ln(n + g + \delta)$	-0.0141 (0.02)	-0.08 (0.23)	0.1296 (0.10)
Education (ln)	0.2543** (0.10)	0.25*** (0.10)	0.4820** (0.22)
Constant	0.4991* (0.32)	0.47** (0.24)	0.5785 (0.49)

Notes. (1) Dependent variable in models (7)-(10): ln(GVA_t)-ln(GVA_{t-1}); (2) *** p<0.01, ** p<0.05, * p<0.1; (3) 2SLS and GMM instruments: first and second Lag of the variables: GVA, investment and school years (4) The resulting standard errors are consistent with panel-specific autocorrelation and heteroskedasticity in one-step estimation.

Despite the lack of convergence suggested by the descriptive analysis, all regression models whose results are presented in Tables 4 and 5 indicate the achievement of both the unconditional and conditional convergence.

In the last part of the empirical analysis, non-parametric methods are used to examine the GVA density distribution from 2007 to 2013. The kernel density, the *dip* test and the stochastic kernel distribution are the main techniques used here.

As shown in Figure 2, the kernel density is found to be unimodal when pooling all data from 2007 to 2014. This result is also confirmed by the *dip* test, not only when pooling all data (from 2007 to 2014), but also for each year in part. This constant result, revealed by both the kernel density estimates and the *dip* test, doesn't indicate that the convergence analysis should be placed into the non-parametric framework. The space of parametric models seems to be appropriate. We ignore this result and continue examining the stochastic kernel distribution. This allows representing the pattern of the GVA transition over our time period.

Figure 2

Kernel density estimates 2007-2013, provincial level

| Period of analysis	Dip value/ p
2007	0.055/ 0.87
2008	0.054/ 0.89
2009	0.075/ 0.53
2010	0.073/ 0.58
2011	0.053/ 0.90
2012	0.054/ 0.88
2013	0.064/ 0.75
2014	0.059/ 0.83
Pooled observations	0.018/ 0.98
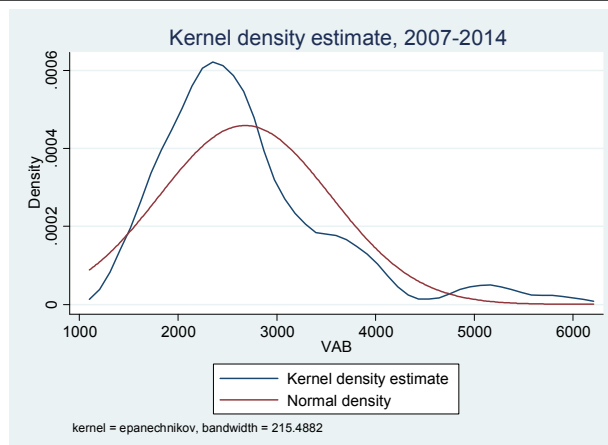
The stochastic kernel density distribution is revealed by contour plots and tri-dimensional charts. In order to facilitate a better understanding of the convergence dynamics from 2007 to 2014, this time interval was split into two sub-intervals, 2007-2010 and 2010-2014. In Figure 3 (a)-(d), the contour plots and three-dimensional representation of the GVA density distribution suggest the formation of a principal convergence club and three small secondary clubs, from 2007 to 2014. With these very small clubs emerging around the main mode, the distribution cannot be defined as purely unimodal, as was resulted from the kernel density and *dip* values.

Both transitions presented in Figure 3, 2007-2014 (Fig.3a and Fig.3c) and 2010-2014 (Fig. 3b and Fig.3d), reflect the existence of four peaks (one principal peak and three smaller ones) that had the same relative position into the GVA density distribution in 2010, as well as in 2014. The main peak is connected to the lowest one (denoting the poor provinces), and only partially to the higher one (denoting the richer provinces). Apart from them, the last peak groups together a small number of provinces that have been and continue to be much richer than the rest. The lowest peak tends to convergence to the principal one, but this process doesn't finish in 2014. The situation of provinces that belong to the lowest peak has clearly improved over the period of analysis, as they slightly migrated upwards toward the principal one. This upward transition reflects a positive convergence pattern.

When comparatively examining both time intervals, all four convergence clubs mentioned above are much flatter and tight in 2010-2014 (Fig.3d) than in 2007-2014 (Fig.3c). This indicates that from 2007 to 2010 all provinces migrated toward the four clubs, contributing therefore to the GVA polarisation. Within this process, some provinces got worse relative positions, while others got better ones. At this point, the most interesting dynamic regards the transitions within the principal convergence club. Initially this one was much larger, but from 2007 to 2010 a group of provinces that were situated above the mean of GVA distribution moved downward toward the mean. In 2010 these provinces are worse off than in 2007, and this illustrates a negative convergence pattern.

Figure 3

Stochastic kernel, provincial level, 2007-2014
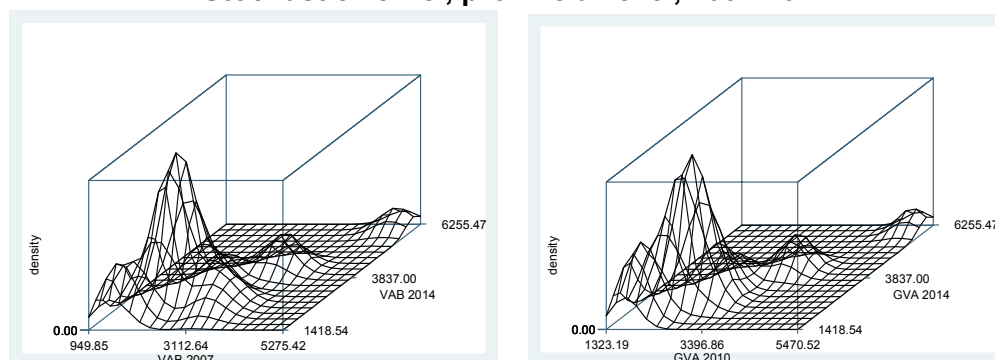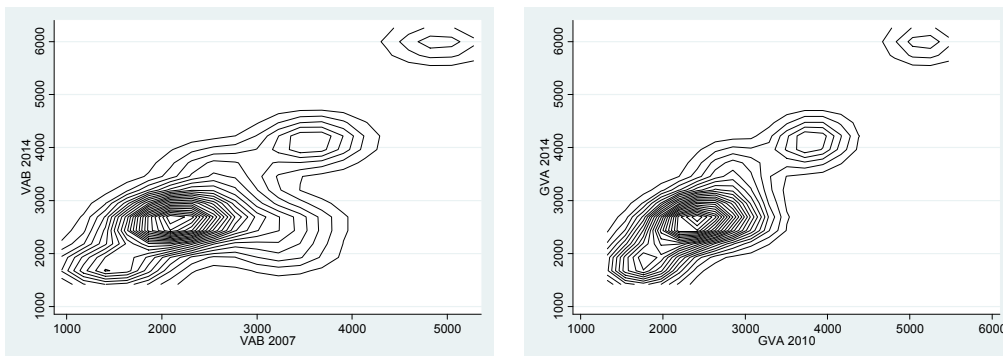
The GVA average levels of four convergence clubs in 2007, 2010 and 2014 show that all clubs have moved toward the richest one, but this one has also become even richer. However, the progress of the lowest club toward the principal one represents in our opinion the most important and positive convergent transition.

The non-parametric analysis of the GVA density distribution transitions within our period of analysis reveals new empirical insights over the parametric models. First, the analysis identifies four convergence clubs, of which just two seem to convergence over time. The upward transition of the group of poor provinces represents the most important and positive transition that develops within the convergence process. But this positive transition is only a small piece into the big framework of the GVA density distribution. Moreover, the provinces tend to tightly concentrate around the four modes, which indicate not only positive convergent dynamics, but also negative ones. The biggest price of the regional convergence in Ecuador could be seen as the worsening of the relative position of the most dynamic group of Ecuadorian provinces (those that were above the mean in 2007 and ended up in being below it in 2010 and 2014).

VI. Conclusions

As mentioned in Introduction, the aim of this paper was the assessment and analysis of regional economic convergence in Ecuador. Even though this topic has previously been approached in Ecuador, there is a clear disagreement between the evidence of "convergence" identified with parametric models (Mendieta Muñoz, 2015a, Mendieta Muñoz and Pontarollo, 2015b) and the high economic heterogeneity reflected by simple descriptive analyses, as well as mentioned by previous papers and articles (e.g. Mendieta Muñoz and Pontarollo, 2015b). The main idea of this paper was that combining the empirical results provided by the parametric and non-parametric approaches could provide a comprehensive picture of regional convergence in Ecuador, which could accommodate and explain all the specific peculiarities of this complex process.

The results as well as the approach followed in our paper are completely new in the literature. As previous papers, this study finds evidence of absolute and conditional convergence at both the cantonal and provincial levels, but the novelty of our papers consists of (1) providing an "in-depth" explanation of the non-linearities involved into the

convergence process, and (2) identifying a set of policy measures that could speed up regional convergence and growth. A closer monitoring of agricultural credits and of their long term effects, the stimulation of the private sector expansion by increasing the number of employees in this area, the increase of public investment effectiveness, as well as encouraging young generation to stay more years in education are found to contribute to the provinces' economic growth and convergence. Using more estimators and two different sets of data provide consistency and robustness to our empirical results.

The non-parametric analysis brings new insights to the convergence process (also confirmed by the descriptive analysis). The regional economy is characterised by a large economic heterogeneity. Out of 24 Ecuadorian provinces, 4 are usually accounted in the literature as outliers (Galapagos and three petroleum provinces). The "outliers" apparently are rich provinces, but their richness has always migrated toward to the really "rich" provinces in Ecuador. The richest provinces in Ecuador (Pichincha, Guayas and Azuay) had always a better relative position in comparison with the others. From 2007 to 2014, but especially from 2007 to 2010, the poorest Ecuadorian provinces forming the lowest convergence club have moved toward the principal convergent club of the majority provinces. Beside this positive convergence pattern, other convergent dynamics also occurred over time, and some of them are rather negative ones. For instance, a group of provinces that in 2007 were situated above the mean GVA migrated downward, toward the main convergence club, by 2010-2014. In this light, the regional economic convergence can be explained by the upward migration of the lowest club to the principal one, but equally by the tight concentration of provinces around the main three clubs. Despite the progress done at the bottom of GVA distribution, the richest provinces (that belong in our non-parametric model to two separate convergence clubs) do not converge with the majority, thus feeding up the tendency of GVA polarisation at the provincial level.

In conclusion, addressing the large economic disparities in Ecuador is strongly needed in the near future. Better regional policies could enhance not only the regional convergence, but the national economic growth as well. Some effective policy measures are discussed in this paper, but definitely their area is much broader. This empirical attempt has proved that using together parametric and non-parametric models allows better diagnosing and understanding complex processes, that otherwise, when being approached in the framework of a single methodology, might be under evaluated.

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