DT
DECON

DOCUMENTO DE TRABAJO

Nº 478

PERU'S REGIONAL GROWTH AND CONVERGENCE IN 1979-2017: AN EMPIRICAL SPATIAL PANEL DATA ANALYSIS

Juan Palomino y
Gabriel Rodríguez

DEPARTAMENTO DE ECONOMÍA

ET LUX IN TENEBRIS LUCET
MCMXVII
100 años PUCP

DOCUMENTO DE TRABAJO N° 478

Peru's Regional Growth and Convergence in 1979-2017: An Empirical Spatial Panel Data Analysis

Juan Palomino y Gabriel Rodríguez

Marzo, 2019

DEPARTAMENTO
DE **ECONOMÍA**

DOCUMENTO DE TRABAJO 478
http://files.pucp.edu.pe/departamento/economia/DDD478.pdf

Peru's Regional Growth and Convergence in 1979-2017: An Empirical Spatial Panel Data Analysis
Documento de Trabajo 478

Editado e Impreso:
© Departamento de Economía – Pontificia Universidad Católica del Perú,
Av. Universitaria 1801, Lima 32 – Perú.
Teléfono: (51-1) 626-2000 anexos 4950 - 4951
econo@pucp.edu.pe
http://departamento.pucp.edu.pe/economia/publicaciones/documentos-de-trabajo/

Encargado de la Serie: Jorge Rojas Rojas
Departamento de Economía – Pontificia Universidad Católica del Perú,
jorge.rojas@pucp.edu.pe
Primera edición – Abril, 2019.
Tiraje: 50 ejemplares

Hecho el Depósito Legal en la Biblioteca Nacional del Perú Nº 2019-06666.
ISSN 2079-8466 (Impresa)
ISSN 2079-8474 (En línea)

Se terminó de imprimir en junio de 2019.

Peru's Regional Growth and Convergence in 1979-2017: An Empirical Spatial Panel Data Analysis

Juan Palomino
Pontificia Universidad Católica del Perú

Gabriel Rodríguez
Pontificia Universidad Católica del Perú

Abstract

This paper analyzes the process of spatial convergence of growth in Peru's 24 regions over 1979-2017. We perform an exploratory analysis of spatial data with global and local statistics, such as Moran I, to provide empirical evidence of spatial dependencies in regional per capita GDP. We then estimate the convergence equation using spatial panel models that control for spatial heterogeneity and spatial interdependence, as well as other structural economic features at the regional level. The empirical results show that spatial convergence is a very reliable conclusion over this period, and prove that spatial regional per capita GDP spillovers play an essential role in determining growth at the local level. Furthermore, the Spatial Durbin model is preferred in the formation of four clusters of convergence. The first cluster is highly productive and dynamic; the second cluster is composed by Jungle and negative-productivity regions; the third cluster is formed by moderately productive and Coast regions; and the fourth cluster is composed by stagnating and Highland regions. Finally, these results may be instrumental in giving greater focus to long-run government policies targeting stagnant and poor regions.

JEL Classification: C21, C23, R11.

Keywords: Regional Convergence; Regional Spillovers; Spatial Dependence Modeling; Spatial Panel Data Models; Clusters of Convergence.

Resumen

Este documento analiza el proceso de convergencia espacial del crecimiento en las 24 regiones de Perú durante 1979-2017. Realizamos un análisis exploratorio de datos espaciales con estadísticos globales y locales, como Moran I, para proporcionar evidencia empírica de dependencias espaciales en el PIB per cápita regional. Luego estimamos la ecuación de convergencia utilizando modelos de paneles espaciales que controlan la heterogeneidad espacial y la interdependencia espacial, así como otras características económicas estructurales a nivel regional. Los resultados empíricos muestran que la convergencia espacial es una conclusión muy confiable durante este período y demuestra que los desbordamientos espaciales regionales per cápita del PIB desempeñan un papel esencial en la determinación del crecimiento a nivel local. Además, el modelo de Durbin espacial es elegido y usado para la formación de cuatro grupos de convergencia. El primer grupo es altamente productivo y dinámico; el segundo grupo está compuesto por regiones de la Selva con productividad negativa; el tercer club está formado por regiones moderadamente productivas y costeras; y el cuarto grupo está compuesto por regiones estancadas y de la Sierra. Finalmente, estos resultados pueden ser fundamentales para prestar mayor atención a las políticas gubernamentales a largo plazo dirigidas a las regiones estancadas y pobres.

Clasificacion JEL:C21, C23, R11.

Palabras Claves: Convergencia Regional; Regional Spillovers; Dependencia Espacial; Modelos Espaciales de Datos de Panel; Clubes de Convergencia.

Peru's Regional Growth and Convergence in 1979-2017: An Empirical Spatial Panel Data Analysis[1]

Juan Palomino[2]
Pontificia Universidad Católica del Perú

Gabriel Rodríguez[3]
Pontificia Universidad Católica del Perú

1 Introduction

Research is increasingly emphasizing the spatial dimension of economic topics. The importance of taking spatial effects into account is extensively reviewed by Anselin (2013). Since then, a growing literature has shown the importance of addressing the problem of errors, as well as the misspecifications that may occur if spatial issues are ignored in data analysis involving geographical units. Among these issues, a prominent subject in macroeconomic literature that falls within this approach is economic convergence. The proposed methodology suggests that the econometric analysis of regional convergence should consider the possibility of spatial dependence between regions. See, among others, Fingleton (1999); Rey and Montouri (1999); Moreno Serrano and Vayá Valcarce (2002); and Pfaffermayr (2012).

Previous studies for Peru, such as Gonzales de Olarte and Trelles Cassinelli (2004); Chirinos (2008); del Pozo and Espinoza (2011); Delgado and del Pozo Segura (2011); and Delgado and Rodríguez (2015) estimate the convergence rate and test if there is convergence among regions. A common characteristic of these studies is that they do not test for the presence of spatial effects in the process of convergence among regions. It is possible, however, that if Peru's regions are spatially correlated, the rates of convergence found in these papers could be biased. In several studies for different countries, the issue of convergence has been studied; see Aroca and Bosch (2000); Badinger et al. (2004); Magalhães et al. (2005); Lundberg (2006); Buccellato (2007); and Asuad Sanén and Quintana Romero (2010). These findings reveal considerable variability in the outcomes, with periods of convergence but little evidence of long-run tendencies. In Latin American countries like Peru, a significant concentration of economic activity in one or more regions presents a challenge in modeling convergence. The case of Peru is further complicated by the markedly uneven distribution of economic activity among regions.

This research reconsiders the question of regional per capita GDP convergence from a spatial econometric perspective and aims at two central objectives. The first one is providing new insights into the geographical dynamics of Peru's regional growth patterns using methods of exploratory spatial data analysis. The second one is proposing the estimation of convergence in per capita GDP across Peru's regions by using panel-data models such as the Spatial Autoregressive Model with Autoregressive Disturbances (SARAR), the Spatial Lag Model (SLM), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM) for 1979-2017; see Elhorst (2003); Millo and Piras

[1] This paper is drawn from Juan Palomino's thesis for the Department of Economics, Pontificia Universidad Católica del Perú (PUCP). We thank the useful comments of Efraín Gonzales de Olarte (PUCP), Pedro Herrera (Ministry of Economy and Finance of Peru), and Paul Castillo (Central Reserve Bank of Peru and PUCP). Any remaining errors are our responsibility.

[2] Juan Palomino. PUCP, Lima, Perú, Telephone: +511-986456469. E-Mail: juan.palominoh@pucp.pe

[3] Address for correspondence: Gabriel Rodríguez, Department of Economics, Pontificia Universidad Católica del Perú, Av. Universitaria 1801, Lima 32, Lima, Perú, Telephone: +511-626-2000 (4998), E-Mail Address: gabriel.rodriguez@pucp.edu.pe.

(2012); and Anselin (2013). This will allow us to extend the traditional β-convergence model to include a rigorous treatment of the spatial correlation between the intercept terms. The value added of this research is that it considers the geographical-spatial effect in regional convergence models; and uses a longer period for a better analysis. Along these lines, it attempts to answer the questions: (i) is it possible to identify a spatial convergence of per capita GDP in Peru's regions over 1979-2017?; (ii) are Peru's regions spatially interdependent?; (iii) what is the role of spatial factors in the growth and formation of convergence clubs? From these questions, our hypothesis is that there is a spatial convergence of per capita GDP due to the spatial dependence between regions; and that spatial effects determine regional growth through contiguity.

The results of our exploratory spatial data analysis indicate that Moran's statistics are significant for most of the period under study; and, therefore, there is spatial autocorrelation in per capita GDP across Peru's 24 regions. While the results of the estimates of spatial panel-data models show that spatial effects are, in fact, relevant and based on the lower value of the AIC and BIC, our preferred model is the SDM for the entire period. The results also show the formation of four clusters of convergence. The first cluster is highly productive and dynamic (Lima and Moquegua); the second cluster is composed by negative-productivity regions (Amazonas, Loreto, and Madre de Dios); the third cluster is composed by moderately productive regions (Áncash, Arequipa, Ica, Junín, Lambayeque, La Libertad, Puno, Tacna, and Tumbes); and the fourth club is formed by stagnant growth regions (Apurímac, Ayacucho, Cajamarca, Cuzco, Huancavelica, Huánuco, Pasco, Piura, San Martín, and Ucayali).

The remainder of this paper is organized as follows: Section 2 shows a brief literature review. Section 3 provides an overview of spatial patterns in the geographic distribution of per capita GDP across the 24 regions in 1979-2017. Section 4 introduces the methodology and data used for quantifying the spatial spillovers of regional per capita GDP. Section 5 reports the test results for the spatial interdependencies of per capita GDP and discusses the estimation results obtained from the spatial panel model. Finally, Section 6 concludes with the main findings and policy implications.

2 Brief Literature Review

Several types of convergence have emerged in the literature, each one being analyzed employing different methods. This section presents the convergence concepts and methods discussed in the economic growth literature.

The first convergence concept is σ-convergence, where the standard deviation or the coefficient of variation is used to measure the cross-sectional dispersion of per capita income over time. This form of convergence has attracted much attention in the regional science and economic geography literature; see Williamson (1965); Bernard and Jones (1996); and Carlino and Mills (1996). The main idea is that a decrease (increase) in the standard deviation suggests convergence (divergence); see Barro et al. (1991).

The second form of convergence occurs when poor regions tend to achieve faster growth than the rich ones, resulting in all regions reaching the same steady state. To test this form of convergence, several studies have employed a cross-sectional specification using ordinary least squares; see Baumol (1986) and Barro and Sala-i-Martin (1992, 2004). This kind of convergence has been labeled as β-convergence and has been used to interpret a negative estimate for β as support for the absolute convergence hypothesis, since it suggests that income growth rates over the period under study are negatively correlated with initial income. This hypothesis has been criticized by theoretical and empirical studies in recent decades. Some criticisms come from Barro and Sala-i-

Martin (1992), who used some extensions of the neoclassical model and proposed that there is a conditional convergence; i.e., regions converge to their own steady state. For instance, Nagaraj, Varoudakis, and Véganzonès (2000) find evidence of conditional convergence among India's regions in 1960-1994, as well as convergence between states that share similar features such as financial development, infrastructure, and education.

Regional convergence studies are originally cross-sectional in nature and are estimated using ordinary least squares. For example, Barro (1991) applies a cross-sectional econometric approach to a set of regions in European Union (EU) countries, and concludes that they have a slow (3%) convergence. However, Islam (1995) proposes a change in the assessment of convergence, as cross-sectional studies have an omitted-variable bias, and performs a data panel estimation, concluding that it is possible to control by specific countries and invariant economic features such as the initial technology level.

A third perspective on convergence can be found in the time-series studies by Bernard and Durlauf (1995); Carlino and Mills (1996); Gómez-Zaldívar and Ventosa-Santaulària (2010); and Delgado and Rodríguez (2015). Here convergence requires that the long-run forecasts of income differences between economies tend to 0; that is, economies catch up with each other. As noted by Bernard and Durlauf (1996), this definition does not hold if shocks on individual economies persist into the indefinite future. In the presence of such shocks, the income series would contain unit roots and, because of this stationarity requirement, this concept of convergence is known as stochastic convergence. The results from the cross-sectional (β and σ–convergence) and time-series studies (stochastic convergence) seem to be at odds. Cross-sectional tests (Barro et al., 1991; Barro and Sala-i-Martin, 1992; Mankiw et al., 1992) generally find evidence of convergence, while the time series tests (Quah, 1993; Bernard and Durlauf, 1995) have tended to fail to reject the no-convergence hypothesis.

Hence, as pointed out in the introduction, the economic analysis of regional convergence is focusing increasingly on issues relating to the spatial dimension. The latter is crucial for assessing regional per capita GDP convergence. The literature suggests that the econometric analysis of regional convergence should consider the possibility of spatial dependence among regions; see Fingleton (1999), Rey and Montouri (1999); Moreno Serrano and Vayá Valcarce (2002); and Buccellato (2007). For example, in the case of Europe, Badinger et al. (2004) perform a regional convergence analysis for the EU (196 countries) over 1985-1999. They apply a spatial filter to the variables to isolate spatial dependence; perform calculations using the Generalized Moment Method for dynamic panels; and find a rate of convergence of 7%. Another research by Buccellato (2007) analyzes the convergence of income levels between 77 regions in Russia using spatial dynamic panel models (spatial error and spatial lag) for 1999-2004 to assess the impact of oil production on regional growth. The results show that the convergence speeds from the spatial lag and spatial error models are 10% and 11.6%, respectively. Moreover, variables such as hydrocarbon production, trade openness, and per capita foreign direct investment have a positive and statistically significant impact on economic growth in Russia. Nowadays, the literature on spatial convergence models focuses on observing whether the convergence processes are the same at the national, regional, and local levels. For example, Dapena, Rubiera-Morollon and Paredes (2018) perform a convergence analysis for the EU over 2000-2014 using a Durbin multilevel model with spatial effects. The results indicate that a general process of convergence in the EU coexists with intranational divergence processes, highlighting the relevance of the spatial level of analysis. Furthermore, they emphasize that the relevance of the territorial scale is important for policy decisions due to behavior discrepancies at the national and local levels.

In the case of Latin America, Aroca and Bosch (2000) evaluate the hypothesis of convergence in Chile's growth pattern using spatial lag and spatial error panel models with fixed effects for 1990-1998. They find a rate of convergence of 8.85% with high spatial concentration, where there are two types of spatial clubs; i.e., productive and dynamic vs. lagging regions. Similarly, Asuad Sanén and Quintana Romero (2010) analyze the hypothesis of β-convergence in Mexico's states for 1970-2008 through the geographical proximity between federal states and spatial economic concentration. The study rejects the convergence hypothesis for the entire period, implying considerable regional inequality. Additionally, they divide the series into two sub-periods and estimate a spatial error model for 1970-1986, where the convergence rate is 25.6%. However, estimations for 1986-2008 suggest a lack of convergence between states, pointing to a divergence process and the existence of convergence clubs.

For Peru, studies such as Gonzales de Olarte and Trelles Cassinelli (2004); Sutton et al. (2006); Delgado and del Pozo Segura (2011); and Delgado and Rodríguez (2017) estimate the rate of convergence among regions but do not test for the presence of spatial dependence among them. It is possible, however, that if per capita GDP in Peru's regions are spatially correlated, the rates of convergence found in these papers could be biased. To our best knowledge, there are no applications of this technique with spatial effects in convergence models for Peru.

3 Spatial Patterns of Economic Growth in Peru

This section provides an overview of spatial patterns in the geographic distribution of real per capita GDP (expressed in constant prices 2007) and economic inequality across Peru's 24 regions in 1979-2017.

3.1 Economic Growth and Geographic Distribution

Peru has experienced a sharp rise in GDP since 1979. Figure 1 shows that the annual per capita GDP has increased at an annual rate of 1.002% in 1979-2017. However, per capita GDP has not grown uniformly across regions: since the 1990s the Coast has experienced greater intrarregional economic activity due to a more extensive road infrastructure, which facilitates economic integration, and to the expansion of agro-export industries throughout the entire region; see Eguren (2003). Although growth performance in the Jungle and Highland regions has been different during the period under study (particularly during the 1980s, when per capita GDP in the Jungle began to fall steadily until 1993), since 2000 a positive grow trend has emerged. However, growth in both regions remained lower than in the Coast, even during the years following the liberalization reforms, mainly because the latter affected the predominantly low-productivity agriculture in the Highlands and Jungle, which compete with substitute imports; and export growth of new products in the Coast contracted. As a result, an economic dualism set in, since modern agriculture, with reasonably advanced technologies and high yields, began to concentrate on the Coast; and, at the same time, subsistence and low-productivity agriculture concentrated on the other two regions; see Gonzales de Olarte (2010).

Figure 2 presents the z-score of per capita GDP for Peru's 24 regions in 1979, 2000, and 2017. It shows a clear division, as the majority of regions with above-mean GDP are located in the Coast. Madre de Dios is the only Jungle region with an above-mean per capita GDP in each of those three years. One explanation for this unusually high per capita GDP is the dynamic mining and services activities in this regional economy.

A comparison of the three years reveals some per capita GDP dispersion across regions over time. First, the per capita GDP gap between the top (Moquegua) and bottom regions narrowed between 1979 and 2017. In 1979, Moquegua's average annual GDP was four standard deviations above the mean value, about four times higher that in Amazonas, but fell in 2000 and 2017. This change coincided with the implementation of Peru's liberalization policies in the 2000s, as mentioned previously. Second, most coastal regions experienced faster per capita GDP growth than the Jungle in the 2000s compared with 1979. Although per capita GDP levels in Highland regions were still relatively low in 2017, they were much closer to the mean than in 2000. In contrast, some Highland regions, such as Áncash, Apurímac, and Pasco, experienced relative rises in per capita GDP; in particular, Apurímac was reclassified from low- to high-per capita GDP region in 2017, mainly due to the expansion of mining activities since 2010.

3.2 Regional GDP Inequality

In this sub-section we apply two convergence analyses to identify a possible per capita GDP catch-up process. First, we calculate the β convergence by regressing the average growth rate in 1979-2017 at the initial level. The ordinary least-squares (OLS) method is used for the entire period. The results (Figure 3) show this relationship and verify the existence of an inverse association process; i.e., the poorest regions grew faster (1.17% per year) than rich regions. Moreover, some regions with high per capita GDP and growth regions, such as Moquegua, Arequipa, and Loreto are left out of this relationship, which suggests that they may converge towards their own steady state. Similarly, Huancavelica and Huánuco begin with low income and growth, which suggests a different growth dynamics in these regions.

Next, a σ-convergence analysis is employed to reconfirm the catch-up process. If the σ-convergence drops, it implies the presence of per capita convergence. In addition to the most frequently used summary measure of σ-convergence in the literature; i.e., the coefficient of variation (CV), this study uses four additional sigma convergence indices, as suggested by Monfort (2008): the Gini coefficient, the Atkinson index, the Theil index, and the Mean Logarithmic Deviation (MLD). The results (Figure 4) indicate that there is a pattern of declining per capita GDP dispersion in Peru in absolute terms; i.e., there has been a reduction in economic inequality between regions. The dispersion for the last year (0.52) is smaller than the initial dispersion during the first year (0.71). In the long run the movement of σ is not uniform, as it shows a way towards convergence with a few exceptions, most notably the hyperinflation crisis of 1987-1992 and the political instability episode of 1998-2001, where an increase in dispersion occurred. After these years, there has been a somewhat modest reduction in regional inequality. This finding is in line with the β convergence estimations in Figure 3, confirming that regional per capita GDP converged over 1979-2017.

4 Methodology and Data

This section discusses the typology of spatial convergence models and the description of variables for the estimation.

4.1 Spatial Econometric Model

To test the impact of spatial interactions on local per capita GDP, we estimate the regional per capita GDP equation or convergence model using a spatial panel model that controls for unobserved spatial heterogeneity and spatial interdependence. Following Elhorst (2014), we add regional structure characteristics as explanatory variables in the convergence equation to control for regional composition effects. The equation to be estimated takes the form:

$$\begin{aligned} \Delta \ln y_{it} = & \quad \alpha_i + \rho W_p \ln y_{it} + \beta y_{it-1} + \gamma X_{it} + \epsilon_{it}, \\ \epsilon_{it} = & \quad \lambda W_p \epsilon_{it-1} + \nu_{it}; \quad \nu_{it} \sim N(0, \sigma_\nu^2), \end{aligned} \tag{1}$$

where $\ln y_{it}$ is the logarithm of annual per capita GDP of a region relative to the national average for a vector of 24 regions over 1979-2017; X_{it} is a vector of explanatory variables containing regional structural characteristics which vary according to observations i and time t; W_p is a $NT \times NT$ row-normalized spatial weight matrix with zero diagonal elements, which defines relations of proximity between two regions (i and j); α_i are fixed effects for each one of the regions i; $|\beta| < 1$ is the parameter for convergence speed; and ϵ_{it} is white noise. This equation attempts to verify whether the evolution of per capita GDP between a given region and the national aggregate is associated with the distance that separates the region from the national average in the previous period.

The spatial weight matrix W_p is built from the definition of $I_T \otimes W_N$ of dimensions $(NT \times NT)$, where I_T is an identity matrix of dimensions $T \times T$, and W_N is constructed according to the principle of Queen Contiguity; i.e., regions are considered neighbors if they share a common border or vertex (LeSage and Pace, 2009). This specification is in line with Kelejian et al. (2013) and only takes into account direct interactions between geographical neighbors.

With the definition of this spatial matrix W_p, a series of tests are performed to provide evidence of the existence of spatial autocorrelation in the least squares residuals for panel data. Recently, Anselin, Gallo, and Jayet (2008) also specified the classical Lagrange Multiplier (LM) tests for a spatial panel:

$$LM_{LagSpatial} = \frac{[\epsilon' W_p \Delta \ln y / \widehat{\sigma}^2]^2}{J}, \tag{2}$$

and

$$LM_{ErrorSpatial} = \frac{[\epsilon' W_p \epsilon / \widehat{\sigma}^2]^2}{T \times T_W}, \tag{3}$$

where J and T_W are defined by

$$\begin{aligned} J = & \quad \frac{1}{\widehat{\sigma}^2}[(W_p Y \widehat{\beta})'(I_{NT} - Y(Y'Y)^{-1}Y')W_p Y \widehat{\beta} + T T_W \widehat{\sigma}^2], \\ T_W = & \quad tr(W_N' W_N + W_N' W_N), \end{aligned} \tag{4}$$

where ϵ denotes the residual vector of a pooled regression model without any spatial or time-specific effects or of a panel data model with spatial and/or time period fixed effects; and W_p is the matrix defined above. The null hypothesis is that there is no spatial autocorrelation.

Two spatial terms in equation (1); i.e., a spatially lagged dependent variable ($W_p \ln y_{it}$) and a spatially correlated error term ($W_p \epsilon_{it}$), measure spatial spillovers. The former, captured by parameter ρ, which is the spatial lag parameter ($|\rho| < 1$), represents the direct regional spatial spillover effect of per capita GDP. The latter, captured by parameter λ, which is the spatial error parameter ($|\lambda| < 1$), measures the spillover effect between the unobserved provincial features that may affect per capita GDP.

Moreover, other spatial models may be obtained from this specification. If $\lambda \neq 0$ and $\rho \neq 0$, a spatial autoregressive model with autoregressive disturbance, known as the SARAR model, results from equation (1). A fixed-effect spatial lag model (SLM) is satisfied when $\lambda = 0$ and $\rho \neq 0$, and this assumes that the effect of spatial interdependence is captured by the spatial lag in the growth rate of per capita GDP, that is, ρ. This equation can be expressed as follows:

$$\begin{aligned} \Delta \ln y_{it} &= \alpha_i + \rho W_p \ln y_{it} + \beta y_{it-1} + \gamma X_{it} + \epsilon_{it}, \\ \Delta \ln y_{it} &= (I - \rho W_p)^{-1}(\alpha_i + \beta y_{it-1} + \gamma X_{it} + \epsilon_{it}). \end{aligned} \tag{5}$$

This matrix $(I - \rho W_p)$ can be understood as a Leontief matrix in an input-output context. Additionally, W_p is a matrix that captures spatial "linkages" between regions and ρ is a weighting factor that determines the relevance of those linkages. This leads to the following interpretation: the growth rate of a region depends not only on the initial level of income (y_{it-1}) but is also affected by its own characteristics α_i and random disturbances from the surrounding regions. In terms of input-output, the growth rate of a region is determined by its own characteristics, those of their neighbors (direct effect), and those of their neighbors' neighbors (indirect effect). According to Elhorst (2010), it is recommended to maximize (5) through a concentrated likelihood approach. Furthermore, fixed effects can be recovered when we assume that the steady state is y^*_{it} and $\Delta \ln y_{it} = 0$, so we obtain the following equation:

$$\alpha_i = \frac{1}{T}\sum_{t=1}^{T}(\ln y_{it} - \rho \sum_{i=1}^{N} w_{ij}\Delta \ln y_{it} - \beta y_{it-1} - \gamma X_{it}). \tag{6}$$

Moreover, the appearance of significant fixed effects (α_i) suggests the existence of specific characteristics in each region and, therefore, a trend towards a differential steady state. Note that the spatial panel data approach not only captures different regional fixed effects, but can also be used as a decision rule to form regional convergence clubs. Along these lines, the regions are sorted from highest- to lowest-performing, according to estimated coefficients of their fixed effects, and we proceed to perform the classification.

If $\rho = 0$ and $\lambda \neq 0$, we obtain the spatial error model (SEM). This model assumes that the spatial dependence affects the estimation through the structure model errors. This model is expressed as follows:

$$\begin{aligned} \Delta \ln y_{it} &= \alpha_i + \beta y_{it-1} + \gamma X_{it} + \epsilon_{it}, \\ \epsilon_{it} &= \lambda W_p \epsilon_{it-1} + \nu_{it}; \quad \nu_{it} \sim N(0, \sigma^2_\nu), \\ \Delta \ln y_{it} &= \alpha_i + \beta y_{it-1} + \gamma X_{it} + (I - \lambda W_p)^{-1}_{it}\nu_{it}. \end{aligned} \tag{7}$$

In this case W_p captures linkages of spatial shocks between regions and λ is the weighting factor determining the level of these linkages. This model is interpreted as follows: a shock originating in a region will produce a random realization that not only affects growth in the region but in the neighboring ones, and through them in the entire country-wide system. Again, a concentrated likelihood approach can be adopted to estimate the parameters of the SEM.

On the other hand, there is another model called the fixed effects spatial Durbin model (SDM), expressed as follows:

$$\Delta \ln y_{it} = \alpha_i + \beta y_{it-1} + \gamma W_p X_{it} + \epsilon_{it}. \quad (8)$$

where W_p is included in the explanatory variables. Thus, the average of explanatory variables of contiguous regions could affect per capita GDP growth in a given region.

The selection of the model is based on statistical criteria, which will be discussed later. The choice of a spatial panel model with fixed effects (FE) instead of random effects (RE) is based on the literature and statistical criteria. The literature suggests that the FE model is generally more appropriate than the RE model, since spatial econometricians tend to work with space-time data of nearby spatial units located in unbroken study areas, such as all regions in a country; see Elhorst (2014).[4] Moreover, this research uses a full sample rather than a representative sample of all regions in Peru. Therefore, the FE model provides a better fit than the RE model, as suggested by Wooldridge (2015). To further justify the choice of FE over RE models, this study also employs Hausman's specification test for both non-spatial (Hausman, 1978) and spatial panel models (Mutl and Pfaffermayr, 2011).

4.2 Variables and Data Description

Although much progress has been made in recent times by the Regional Information System of Peru's Institute of Statistics and Information, spatial data availability remains a significant challenge. Data availability is still low and in many instances it is difficult to obtain harmonized datasets allowing consistent regional comparisons. In this research we use data for the log per capita GDP expressed in constant 2007 prices. We have information for the 24 regions for 1979-2017.

The dependent variable in equation (1) is the natural logarithm of annual per capita GDP in region i at time t. The explanatory variables for regional characteristics, denoted by X_{it} in equation (1), are drawn from the literature on regional structural features. This research suggests two possible reasons for spatial variations in per capita GDP growth: (i) economic structure; and (ii) agglomeration.

The regional economic structure is considered an important determinant of per capita GDP growth because it differs across regions for economic reasons and tends to vary through time. Therefore, following Delgado and del Pozo Segura (2011), we include the share of agriculture and manufacturing GDP in region i at time t to identify structural changes in the economic system. The definition of the variables for the shares of agriculture and manufacturing is the percentage of economic activity in region i for each industry. Previous studies have also highlighted the importance of the specialization coefficient; i.e., the degree of similarity of the regional economic structure with the economic structure of the country; see Gonzales de Olarte (2010). When the index is above average, there is "regional specialization" and when it is below the average, there is "regional diversification".

Additionally, an important growth determinant in neoclassical models is the geographical agglomeration of economic activities that can reinforce economic growth. Thus, we add population density to our set of explanatory variables to control for agglomerated regions; see Martin and Ottaviano (2001), Corrado et al. (2005). Variable definitions and descriptive statistics are reported in Table 1. For example, the average regional per capita GDP for 1979-2017 is 9,429 soles, while the sectors with the highest share are manufacturing and services, with 41.6% and 39%, respectively. It should be noted that the coefficient of specialization in this period is low, so on average the regions

[4] Elhorst (2003) provides a thorough survey of the specification and estimation of spatial panel data models, including spatial effects either in the form of error autocorrelation or of a spatially lagged dependent variable.

are diversified. In terms of agglomeration, the population density is 31 inhabitants per km^2. It is expected that the use of these variables will not only allow establishing the effect that certain factors have on spatial convergence, but also providing greater stability to the β coefficient when analyzing it for the whole period.

5 Empirical Results

This section explains the results of the spatial dependence tests used to assess the incorporation of space and presents the results of the spatial models.

5.1 Test for Spatial Interdependencies of Regional per Capita GDP

To test for the spatial interdependencies of regional per capita GDP, we adopt the Global Moran's I statistic proposed by Moran (1950). This statistic has been widely used in the literature on spatial studies, as it is considered useful for measuring the degree to which activities in one location are similar to those in neighboring locations; see, for instance, Ying (2000); Arbia et al. (2005); Guillain et al. (2006); Bai et al. (2012); and Lottmann (2012). The Global Moran's I statistic is calculated by:

$$I = (\frac{n}{S_0})\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - \overline{x})^2}, \tag{9}$$

where n is the number of regions (24 in this study); W_{ij} is the spatial weight matrix as discussed previously; and S_0 is a scaling factor equal to the sum of all the elements of W; i.e., $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}$. Furthermore, x_i is the annual per capita GDP for region i and $\overline{x}$ the mean value of regional per capita GDP. The null hypothesis (H_0) is the absence of spatial autocorrelation in the entire regional system covered by the study. A positive coefficient indicates that contiguous regions have similar per capita GDP levels, with a higher value implying a stronger association. By contrast, a negative coefficient reveals a dissimilar pattern in adjacent regions, with a lower value implying a stronger negative correlation; see Ertur et al. (2006). When there is a balanced coexistence of both types of correlations, the Global Moran's I statistic approaches zero, indicating a random distribution of per capita GDP across observations.

Table 2 shows the results of spatial autocorrelation for regional GDP over the entire period. The results show that the Global Moran's I statistics are positive and highly significant for most years except 1988, 1990, 2009, 2011, 2012, and 2013, indicating a strong and positive spatial interdependences in regional per capita GDP in Peru.[5] That is to say, regions with a similar per capita GDP (high or low) tend to be concentrated geographically. Moreover, the trend of spatial integration of regional per capita GDP is intensified over time, as the Global Moran's I statistic increased from 0.094 to 0.176 between 1979 and 2017.

The above result confirms the hypothesis that the regions cannot be treated as independent observations, but should be seen as a system where space is relevant due to the wide inequality

[5] The chaotic 1988-1990 period was characterized by high inflation, recession, and widespread corruption under the first administration of Alan Garcia. In 2009, exports deteriorated in the wake of the global financial crisis. In 2011-2013, economic measures were introduced to expedite economic recovery.

of GDP between regions. However, the Global Moran's I statistics only reflect the overall trend of spatial autocorrelation; i.e., it fails to identify outliers that run in the opposite direction to the global spatial trend. To address this issue, we follow Anselin (1996) and employ the Moran scatter plot to illustrate the relationship between each observation and their neighbors. The scatter plot provides a visual impression of the overall stability of the global pattern of dependence, as well as the ability to identify local regimes of spatial dependence that may depart from the overall pattern. It is a bivariate scatter plot that places the unit values of per capita GDP for region i ($GDPpc_i$) on the horizontal axis and spatial lag per capita GDP ($lagGDPpc_j = \frac{\sum_{j=1}^{n} W_{ij}GDPpc_j}{\sum_{j=1}^{n} W_{ij}}$) on the vertical axis, and each observation is located in one quadrant of the scatter plot.

Figure 5 shows two Moran scatter plots of regional per capita GDP for the initial (1979) and final (2017) years, which are divided into four quadrants. The regions in Quadrant I represent high-GDPpc regions with high-GDPpc neighbors, and those in Quadrant III low-GDPpc regions with low-GDPpc neighbors. They are labeled 'HH' and 'LL', respectively, and both indicate positive forms of spatial dependence or a spatial cluster of similar per capita GDP. The remaining regions in Quadrants II and IV, labeled 'LH' and 'HL', represent low- and high-GDPpc regions surrounded by high- and low-GDPpc regions, respectively, which can be identified as spatial outliers and indicate negative spatial autocorrelations. In the scatter plots, most regions show that they are positively correlated with their neighbors, since most observations (regions) are in Quadrant III (LL) for both years. However, there are still a few regions that are negatively correlated with their neighbors (points in Quadrants II and IV).

Figure 6 shows maps of Peru's mainland indicating the geographic locations of the points in the Moran scatter plot for 1979 and 2017 in Figure 5. Consistent with the findings shown in Figure 2, both maps illustrate a clear division between Coast, Highlands, and Jungle. A comparison of those two maps reveals four relevant findings. First, the regions with high per capita GDP and similar high-GDPpc neighbors are Moquegua and Tacna, which are concentrated in the South Coast of Peru in 1979. Second, the number of high-GDPpc regions located in the South Coast increased from two to five between 1979 and 2017. Third, the regions with per capita GDP below the average and poor neighbors are located in the North Coast and South Highlands in 1979. Fourth, this number of regions in this cluster decreased from 14 to 11 by 2017, thereby moving the concentration of poor regions towards the northern Jungle, Highlands, and Coast.

Next, a slightly different perspective from the scatter plot is provided by the Local Indicators of Spatial Autocorrelation (LISA) developed by Anselin (1995). We employ LISA to test for the significance of local association for each region in the Moran scatter plots because only significant LL regions can be considered economic cores of low per capita GDP, as explained by Guillain et al. (2006). The LISA statistic takes the following form:

$$I_i = \frac{\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i}^{n}(x_i - \overline{x})^2}, \tag{10}$$

where I_i represents the LISA of region i and the other symbols are the same as those in the Global Moran I statistic.

Figure 7 illustrates the significance levels for each region in the Moran scatter plot. Although the majority of regions show insignificant association with their neighbors (i.e., those shown as non-colored regions), the few statistically significant ones reveal two interesting findings. First, Cajamarca's low dynamism is due to its high dependence on agriculture and mining. Over the period under study these sectors contracted as a result of adverse policies implemented in the region, making it one of the least productive. Second, the map in Figure 7 shows that, in 1979, all significant LL regions were located in the North Coast of Peru, while in 2017 the significant LL regions were in the North Coast, Highlands, and Jungle.

The results from the application of the local Moran statistics to GDP values in each year of the sample are summarized in Table 3. The number of years for which the local statistic provides indications of clustering using a pseudo-significance level of $p - value < 0.01$ is reported in each column. The first conclusion is that the local pattern of spatial association tends to reflect the global trend of positive spatial association reported earlier. More specifically, local significant indicators are in quadrant III of the scatter plot, reflecting LL clustering. The second conclusion is that one strong regional clusters seem to be persistent throughout the 39 years. This cluster includes the northern regions of Amazonas, Cajamarca, La Libertad, Loreto, and San Martín. The results provide fairly strong evidence that clustering in these regions is not due to chance alone.

5.2 Parameters Estimates from Non-Spatial Panel Models

Our empirical analysis starts with a traditional panel regression analysis across Peru's 24 regions for 1979-2017. The estimation results from the non-spatial panel data models are presented in Table 4. Columns (1) to (4) are those for the pooled OLS, the time period-fixed effect, region-fixed effect, and two-way (both region- and time period-fixed effect) models, respectively. Hence, we perform estimates of β convergence. If convergence holds, we would expect a negative and significant coefficient for the variable referring to the initial condition. The results show that for the four specifications, β convergence is a significant coefficient and very strong in magnitude. For instance, the coefficient of β convergence for regional fixed effects is -0.133, which is lower than the coefficient of the two-way fixed effects (-0.208). These results indicate that there is a long-run convergence among Peru's regions. Compared with other studies that use β convergence with the same territorial scale, this coefficient is higher than reported by Delgado and del Pozo Segura (2011) and Sutton et al. (2006) for Peru.

However, we perform a likelihood ratio (LR) test to verify the time- and region-fixed effects. The LR test for the joint insignificance of the time-period fixed effects is rejected (179.14, $p < 0.01$). Similarly, that for the joint insignificance of the region-fixed effects is also rejected (153.41, $p < 0.01$). These results suggest the extension of a fixed-effect model with both region-fixed and time-period fixed effects as in Baltagi (2008), implying that specification (4) in Table 4 is the preferred non-spatial panel model. This choice is also justified by the results from the LR test shown in the last column of Table 4. Moreover, in the lower part of the Table, we report results of a Hausman test (Hausman, 1978) comparing the specifications of the β convergence estimates. This test allows us to discern which fixed effects are preferable. In this case, it states that the random effect suffers from inconsistency because the p-value is lower than 0.05 and, hence, a fixed effect is a better choice.

However, if spatial interdependence exists within the panel data, non-spatial panel models may lead to biased and inefficient parameter estimates, given the omission of spatial interactions among observations; see Franzese and Hays (2007). To test for the presence of spatial interaction effects in our panel model, we follow Anselin et al. (2008) in conducting a Lagrange Multiplier (LM) test for a spatially lagged dependent variable ("LM spatial lag") and a spatial autocorrelated error term ("LM spatial error"). The results show that throughout 1979-2017, the classic LM test rejects the null hypothesis of no spatial autocorrelation in the dependent variable ($LM_{Lag} = 8.02$ with $p - value = 0.004$) and the hypothesis of no spatial autocorrelation in the error term ($LM_{Error} = 8.885$ with $p - value = 0.003$). The first version is very powerful against spatial dependence, both in the form of error autocorrelation and spatial lag; but does not allow discriminating between the two alternative forms of misspecification; see Millo and Piras (2012). Both LM tests have high values and are significant. These results are consistent because in the period under study there was a growing dependence between regions, as shown by the results of the exploratory spatial data analysis discussed in the previous Section.

5.3 Parameters Estimates from Spatial Panel Models

Comparing the estimation coefficient in the fixed-effect model without spatial effects, Table 5 reports the estimated results from spatial panel models. Columns (1) to (4) report the estimation results from the SEM, SLM, SARAR, and SDM, respectively. First, to verify whether fixed effects provide a better fit to the spatial panel model than random effects, we conduct the spatial Hausman test for each model. The results, shown at the bottom of Table 5, suggest that random effects should be rejected, and thus verify that the spatial panel model with fixed effects is preferred.

The results also verify that there is spatial convergence for each model because the significant coefficient of β indicates that there is a negative relationship between the initial per capita GDP and its growth rate for all models. Moreover, the speed of convergence is such that the average region reduces the gap between per capita GDP and their steady state by approximately 13.3% each year for the SLM. A similar pattern can be observed in the estimated coefficients for SEM, SARAR, and SDM models, whose β coefficients are 13.9%, 14.8%, and 18.2%, respectively. Consequently, the half-life of convergence (the average time necessary to eliminate the gap) is 5 years for all models.[6] As expected, the results for spatial β convergence show that space plays a main role in the mandate to create new macro-regions due to the heterogeneous process of convergence among groups, with the outcome being a set of convergence clubs.

Taking a closer look at the differences between spatial parameters, one can observe interesting patterns. For instance, the spatial parameters of the SARAR model are both significant, but the spatial lag coefficient (ρ) is negative and the spatial error coefficient (λ) is positive. On the contrary, when we compare the spatial lag parameters of the SLM and SDM models, ρ is positive and significant. The interpretation of this parameter ρ indicates that the average log of per capita GDP in contiguous regions has a positive impact on local per capita GDP. In the SEM model, the spatial error coefficient λ is positive and significant at 1% level, and the interpretation from an economic perspective is that a shock produced in a region affects not only the local region but also contiguous regions; i.e., a shock affecting one region creates positive spillovers on its neighbors. Finally, based on AIC and BIC, our empirical research shows that the fixed-effect SDM is preferred. According to Lesage and Pace (2009), this model reduces the omitted-variable bias compared to ordinary least squares (OLS), which is an important motivation for using it in empirical research. Furthermore, this model has the main advantage that our dependent variable is related to spatial lags of both the dependent and independent variables.

Apart from the parameters for the spatial variables, the parameter estimates for the other explanatory variables are also informative. First, economic activity variables play important roles in the determination of per capita GDP growth. The local share of agriculture and manufacturing

[6] See Arbia (2006) for further details concerning half-life issues.

in the region are found to have significant positive impacts on local growth rates for all spatial models. For example, a 1% increase in the regional share of agriculture leads to a 0.412% growth rate increase, while a 1% increase in the share of the regional share of manufacturing has a positive 0.320% impact on the growth rate using the SDM. Similarly, the positive and significant parameter for the specialization coefficient indicates that there has been an increase in the specialization of activities in the regions over the period under study. For instance, if the specialization coefficient increases by 1%, the average local per capita GDP growth will increase by 0.157%. On the contrary, a 1% increase in regional population density will decrease per capita GDP growth by 0.114%. Additionally, the SDM presents the results of spatially lagged explanatory variables for the contiguous regions. In this case, per capita GDP of the neighboring regions positively affects the growth rate, and the agriculture share of the neighboring regions negatively affects the local region.

In these estimations there are also the fixed parameters α_i, which isolate the effect of omitted variables, representing different structural characteristics of the regional economies. For this reason, Table 6 shows the steady states by regions obtained from the SDM model for 1979-2017. For example, the steady state coefficient for Lima is 2.5, twice as large as the steady state for Amazonas (-2.014). With these steady state values we form spatial convergence clubs, which are presented in Panel A of Table 7. The first convergence club, formed by Lima and Moquegua, is highly productive and dynamic. The second convergence club is composed by negative productivity regions such as Amazonas, Loreto, and Madre de Dios. The third club is composed by moderately productive regions such as Áncash, Arequipa, Ica, Junín, Lambayeque, La Libertad, Puno, Tacna, and Tumbes. The fourth club is formed by stagnant growth regions (Apurímac, Ayacucho, Cajamarca, Cuzco, Huancavelica, Huánuco, Pasco, Piura, San Martín, and Ucayali).

We compared our results with the findings of the convergence clubs of Delgado and Rodríguez (2015), whose methodology is based on the time series tests of Phillips and Sul (2009), shown in Panel B of Table 7. They evaluate a different period (1970-2010) without considering Ucayali. In contrast, our methodology criterion is of spatial proximity, which reflects the interaction between the economies of all regions. These comparisons can be visualized in the maps presented in Figure 8. For example, our first club of regions (Lima and Moquegua) is included in their Club 1. Meanwhile, our Club 2, formed by Jungle regions (Amazonas, Loreto, and Madre de Dios) are scattered among their Clubs 1, 2, and 3. The regions in our Club 3 (Ancash, Arequipa, Ica, Junín, Lambayeque, La Libertad, Puno, Tacna, and Tumbes) are in their Club 2. Finally, regions in their Club 4 (Apurímac and Huánuco) are in our Club 4 (low-productivity regions). In conclusion, our convergence clubs are characterized by being spatially contiguous in productivity.

In addition to this comparison of different methods of forming convergence clubs, the curves of relative per capita GDP for each club and their production structure are presented in Figures 9a-12b to evidence the consistency among these convergence clubs over time. Figure 9a shows the regions that are part of the first convergence club, which are bridging their differences and approaching a single steady state. Furthermore, Figure 9b shows that Lima has diversified its economy because it increased its share in the industrial sector and reduced its share in the services sector over the period under study, while Moquegua has specialized over time by reducing from 86% to 76% its share in the industrial sector, while its share in the services sector has risen from 8% to 16%. These regions have little participation in the agriculture and construction sectors, although in Lima the construction sector increased from 2.8% in 1979 to 5.2% in 2017 due to higher public investment in road infrastructure.

Figure 10a shows the Jungle regions of Amazonas, Loreto, and Madre de Dios, included in the second convergence club (the least productive regions). We can observe that Loreto's per capita

GDP decreased due to the loss of the oil canon, which reduces the Regional Government's budget for executing public works; see National Institute of Statistics and Information (2017). Similarly, Madre de Dios's GDP has decreased over time, explained by a decrease in mining due to interdiction actions against illegal mining. Additionally, Figure 10b shows that the sectors that have contributed the most to growth in the three regions are agriculture and services in 2017, unlike the construction sector, which still has a low share, even though in recent years there has been more public and private investment.

The production structure of the third convergence club is presented in Figures 11a and 11b. These regions concentrate in the Coast and have greater production diversification, with higher participation in manufacturing and services. The fourth convergence club is focused on the northern and southern highlands of Peru, and the evolution of per capita GDP is presented in Figure 12a. For instance, Pasco's GDP had an increasing trend until the end of 2000, but then it started to contract. Another particular case is Apurímac, which began with a low per capita GDP, reversed this trend over the last five years and started to converge within the club. Moreover, previous studies as Delgado and del Pozo Segura (2011), Delgado and Rodríguez (2015) indicate that Apurímac and Huánuco are the most vulnerable regions due to low productivity. However, Apurímac is one of the regions that has contributed most to Peru's growth in recent years (2.5% according to the National Institute of Statistics and Information, 2017). The main reason is the momentum of the mining subsector, where copper, gold, and silver production increased. The agricultural subsector also showed a positive performance due to higher production of corn, maize, and quinoa in a context of favorable weather conditions. Thus, Apurímac will likely no longer be considered a vulnerable region in the coming years. Figure 12b shows that the industrial sector, especially mining, has greater participation in the Cuzco, Huancavelica, and Pasco regions. Likewise, the services sector is more concentrated in the Ayacucho, Cajamarca, San Martin, and Ucayali regions.

5.4 Direct and Indirect Effects of Explanatory Variables

Previous studies may have only used the estimated coefficient of the spatial lagged dependent variable (ρ) to test the hypothesis as to whether spatial spillovers exist. This may have resulted in incomplete conclusions as the estimated results may diverge in the different specification of spatial regression models; see LeSage and Pace (2009). To address this issue, we apply the partial derivative measures introduced by LeSage and Pace (2009) and Debarsy et al. (2012) to calculate the direct and indirect impacts of all the explanatory variables on the independent variable as a supplementary analysis. Since the SDM has proven the most appropriate model, we confine the simulations to the parameter estimates from the fixed-effect SDM. Table 8 shows the estimated results for the direct, indirect and total (sum of the direct and indirect effects) effects produced by simulating the parameters from spatial panel models using the maximum likelihood multivariate normal parameter distribution and a series of 500 simulated draws.

The direct impact estimates shown in column (2) of Table 8 are similar to the corresponding parameter estimates (in absolute terms) shown in column (2) of Table 5, but the former is slightly larger. Their differences arise because the estimations on direct effects include some feedback loop effects that occur as a result of impacts passing through neighboring regions to a specific region; see Debarsy et al. (2012). If the estimates of the direct impact exceed the parameter estimates, this reflects a positive feedback and vice versa. For example, the direct effect of the share of manufacturing is 0.323, while the estimated coefficient of the share of manufacturing in the SDM is 0.320. As the difference between them is positive (0.003), increases in the share of manufacturing in neighboring regions have a positive impact on growth in a given region. Similarly, two other explanatory variables, i.e., the log of regional population density and the specialization coefficient, have a positive feedback effect, while the share of agriculture has a negative feedback effect.

The indirect effect estimations measure spatial spillovers rather than the coefficient estimations of the spatially lagged dependent variable; see LeSage and Fischer (2008). This can be explained as reflecting how a change in an explanatory variable in all other regions impacts on per capita GDP growth in a given region. The indirect effect estimated for the log of regional population density is positive and significant, indicating that this variable has positive spillover effects on neighboring regions. Moreover, the indirect effect of agriculture is negative, suggesting that a decrease in this activity will not only decrease per capita GDP growth in a particular region but, to a certain extent, also in its contiguous regions. However, the indirect impact of the remaining variables is not statistically significant. In sum, the positive (negative) indirect impacts (or spillovers) arise because changes in those variables positively (negatively) impact per capita GDP growth in their own regions. This, in turn, simultaneously affects per capita GDP in neighbouring regions due to the existence of positive regional GDP spillovers.

Finally, a valid question in spatial econometrics is whether the results are sensitive to the definition of the spatial weight matrix. In order to answer this issue, we perform several robustness checks to show the sensitivity of our main finding. We use a different definition of spatial matrix weights such as Euclidian distance and k-nearest neighbors. The results are very similar with our findings.[7]

6 Conclusions

While the existing literature documents the factors leading to regional per capita GDP disparity, few studies have considered the effect of spatial interactions on local per capita GDP. This study seeks to highlight the pattern of per capita GDP convergence in Peru's regions, as well as examine spatial per capita GDP spillovers on local growth rates using data from Peru's 24 regions over 1979-2017. This study differs from most previous work in this field by considering both spatial heterogeneities through controlling for the fixed effects of each region and spatial interdependence by incorporating a spatial lagged dependent variable and a spatially correlated error term.

Our empirical strategy is based on recent developments in exploratory spatial data analysis, as well as an explicit spatial econometric approach. The overriding finding is that it is possible to provide precise insights as to the geographic dimension of regional GDP growth, as well as new evidence on the role of spatial effects in the formal econometric analysis of regional GDP convergence. The application of standard tests in exploratory spatial data analysis reveals that there is strong evidence of spatial autocorrelation in per capita GDP over the entire period. By examining the spatial patterns of regional per capita GDP in 1979 and 2017, this study finds that low per capita GDP regions are spatially clustered in northern Peru. One possible reason is that low-per capita GDP regions have a negative dispersion effect on their neighboring regions; i.e., per capita GDP spillovers exist across Peru's regions. Therefore, neglecting spatial interdependence when modeling convergence equations leads to biased and inefficient parameter estimates.

Thus, following the work by Elhorst (2003), we estimated four different models of spatial panel data, namely: (a) SARAR, (b) SLM, (c) SEM, and (d) SDM. Our results reveal that estimating spatial convergence through the SDM is more appropriate because it has the advantage that the dependent variable is related with spatial lags for both the dependent and independent variables.

[7] The results of these estimates are available upon request.

Our results reveal that there are four spatial clusters. The first club is formed by dynamic and highly productive regions (Lima and Moquegua). The second club is formed by low-productivity regions (Amazonas, Loreto and Madre de Dios). The third club is composed by moderately productive regions (Áncash, Arequipa, Ica, Junín, Lambayeque, La Libertad, Puno, Tacna, and Tumbes). The fourth club is formed by stagnant-growth regions (Apurímac, Ayacucho, Cajamarca, Cuzco, Huancavelica, Huánuco, Pasco, Piura, San Martín, and Ucayali).

The following policy implications emerge from these findings. First, the presence of significant spatial spillovers indicates that political decisions of local governments affect not only their own regions but also adjacent ones, thereby requiring the central government to pay special attention to coordination across sub-national administrative units. Second, the results reinforce the idea that Peru needs to develop policies for the benefit of stagnant and poor regions, where GDP has declined over time and which are vulnerable because they are close to poor regions. One possible solution is that, if the central administration and/or local governments invest more in infrastructure and education, per capita GDP spillover effects among regions will be even larger. This in turn will help to reduce regional per capita GDP inequality. Thus, efective policies might contribute to promoting growth in Peru.

Future investigations that can be derived from this work are related with the development of new strategies for analyzing the evolution of the distribution of per capita GDP over time and space, using spatial Markov models or non-parametric methods to allow non-linearity in the parameters of the growth process. Finally, it is important to generate solid information at the provincial or district level to develop studies on spatial econometrics with greater emphasis on specific territories within Peru.

References

[1] Anselin, L. (1995), "Local Indicators of Spatial Association-LISA," *Geographical Analysis* **27(2)**, 93-115.

[2] Anselin, L. (1996), "The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association," in Fischer, M., H. Scholten and D. Unwin (Editors), *Spatial analytical perspectives on GIS*, Chapter 8, London, Bristol: Taylor & Francis.

[3] Anselin, L. (2013), *Spatial Econometrics: Methods and Models.* Springer Science & Business Media, Berlin, Heidelberg.

[4] Anselin, L., Gallo, J. L., and Jayet, H. (2008), "Spatial Panel Econometrics," in L. Màtyàs and P. Sevestre (Editors), *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice,* Chapter 18, Berlin, Heidelberg: Springer Berlin Heidelberg.

[5] Arbia, G. (2006), *Spatial Econometrics: Statistical Foundations and Applications to Regional Convergence*, Springer Science and Business Media, Berlin, Heidelberg.

[6] Arbia, G., Basile, R., and Piras, G. (2005), "Using Spatial Panel Data in Modelling Regional Growth and Convergence," ISAE Working Paper **55**.

[7] Aroca, P., and Bosch, M. (2000), "Crecimiento, Convergencia y Espacio en las Regiones Chilenas: 1960-1998," *Estudios de Economía* **27(2)**, 199-224.

[8] Asuad Sanén, N., and Quintana Romero, L. (2010), "Crecimiento Económico, Convergencia y Concentración Económica Espacial en las Entidades Federativas de México 1970-2008," *Investigaciones Regionales* **18**, 83-106.

[9] Badinger, H., Müller, W., and Tondl, G. (2004), "Regional Convergence in the European Union, 1985-1999: A Spatial Dynamic Panel Analysis," *Regional Studies* **38(3)**, 241-253.

[10] Bai, C. E., Ma, H., and Pan, W. (2012), "Spatial spillover and regional economic growth in China," *China Economic Review*, **23(4)**, 982-990.

[11] Baltagi, B. (2008), *Econometric Analysis of Panel Data*, John Wiley and Sons, Hoboken, New Yersey.

[12] Barro, R. J. (1991), "Economic Growth in a Cross Section of Countries," *The Quarterly Journal of Economics* **106(2)**, 407-443.

[13] Barro, R. J., and Sala-I-Martin, X. (1992), "Convergence," *Journal of Political Economy* **100(2)**, 223-251.

[14] Barro, R. J., and Sala-I-Martin, X. (2004), *Economic Growth.* MIT Press, Cambridge, Massachusettes.

[15] Barro, R. J., Sala-I-Martin, X., Blanchard, O. J., and Hall, R. E. (1991), "Convergence Across States and Regions," *Brookings Papers on Economic Activity* **1991(1)**, 107-182.

[16] Baumol, W. J. (1986), "Productivity Growth, Convergence, and Welfare: What the Long-Run Data Show," *American Economic Review* **76(5)**, 1072-1085.

[17] Bernard, A. B., and Durlauf, S. N. (1995), "Convergence in International Output," *Journal of Applied Econometrics* **10(2)**, 97-108.

[18] Bernard, A. B., and Durlauf, S. N. (1996), "Interpreting Tests of the Convergence Hypothesis," *Journal of Econometrics* **71(1-2)**, 161-173.

[19] Bernard, A. B., and Jones, C. I. (1996), "Technology and Convergence," *The Economic Journal* **106(437)**, 1037-1044.

[20] Buccellato, T. (2007), "Convergence Across Russian Regions: A Spatial Econometrics Approach," UCL School of Slavonic and East European Studies (SSEES). Working Paper **72**.

[21] Carlino, G., and Mills, L. (1996), "Convergence and the US states: A Time-Series Analysis," *Journal of Regional Science* **36(4)**, 597-616.

[22] Chirinos, R. (2008), "¿Convergen las Regiones en el Perú? Evidencia Empírica para el Período 1994-2007," XXVI Encuentro De Economistas BCRP.

[23] Corrado, L., Martin, R., and Weeks, M. (2005), "Identifying and interpreting regional convergence clusters across Europe," *The Economic Journal*, 115(502), C133-C160.

[24] Dapena, A., Rubiera-Morollon, F., and Paredes, D. (2018), "New Approach to Economic Convergence in the EU: A Multilevel Analysis from the Spatial Effects Perspective," *International Regional Science Review* https://doi.org/10.1177/0160017618804010.

[25] Debarsy, N., Ertur, C., and LeSage, J. P. (2012), "Interpreting dynamic space–time panel data models," *Statistical Methodology*, **9(1-2)**, 158-171.

[26] Del Pozo, J. M., and Espinoza, L. M. (2011), "Un Análisis Exploratorio de Convergencia en el PIB per Cápita entre Departamentos en el Perú, 1979-2008," in Iguiñiz, J. and J. León (Editors), *Desigualdad Distributiva en el Perú: Dimensiones*, Chapter 4, Lima: Pontificia Universidad Católica del Perú.

[27] Delgado, A., and Del Pozo Segura, J. M. (2011), "Convergencia y Ciclos Económicos Departamentales en el Perú: 1979-2008," Consorcio de Investigación Económica y Social (CIES), Lima.

[28] Delgado, A., and Rodríguez, G. (2015), "Structural Breaks and Convergence in the Regions of Peru: 1970-2010," *Review of Development Economics* **19(2)**, 346-357.

[29] Delgado, A., and Rodríguez, G. (2017), "Convergencia en las Regiones del Perú: ¿Inclusión o Exclusión en el Crecimiento de la Economía Peruana (1970-2010)?," in Francke P. and J. Rodriguez (Editors), *Exclusión e Inclusión Social en el Perú* (249-294), Lima: Pontificia Universidad Católica del Perú.

[30] Eguren, F. (2003), "La agricultura de la costa peruana," *Debate Agrario*, **35**, 1-38.

[31] Elhorst, J. P. (2003), "Specification and Estimation of Spatial Panel Data Models," *International Regional Science Review* **26(3)**, 244-268.

[32] Elhorst, J. P. (2010), "Spatial Panel Data Models," in *Handbook of Applied Spatial Analysis*, 377-407. Springer, Berlin, Heidelberg.

[33] Elhorst, J. P. (2014), "Spatial Panel Data Models," in *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, Springer, Berlin, Heidelberg.

[34] Ertur, C., Le Gallo, J., and Baumont, C. (2006), "The European Regional Convergence Process, 1980-1995: Do Spatial Regimes and Spatial Dependence Matter?," *International Regional Science Review* **29(1)**, 3-34.

[35] Fingleton, B. (1999), "Estimates of Time to Economic Convergence: An Analysis of Regions of the European Union," *International Regional Science Review* **22(1)**, 5-34.

[36] Franzese, R. J., and Hays, J. C. (2007), "Spatial econometric models of cross-sectional interdependence in political science panel and time-series-cross-section data," *Political Analysis*, **15(2)**, 140-164.

[37] Gonzales de Olarte, E. (2010), "Descentralización, Divergencia y Desarrollo Regional en el Perú del 2010," in Rodriguez, J. and M. Tello (Editors), *Opciones de Política Económica en el Perú: 2011-2015*, Chapter 6, Lima: Pontificia Universidad Católica del Perú.

[38] Gonzales de Olarte, E., and Trelles Cassinelli, J. (2004), "Divergencia y Convergencia Regional en el Perú: 1978-1992," *Revista Economía* **27 (53-54)**, 35-63.

[39] Gómez-Zaldívar, M., and Ventosa-Santaulària, D. (2010), "Per Capita Output Convergence: The Dickey-Fuller Test Under the Simultaneous Presence of Stochastic and Deterministic Trends," *Annals of Economics and Statistics* **99-100**, 429-445.

[40] Guillain, R., Le Gallo, J., and Boiteux-Orain, C. (2006), "Changes in spatial and sectoral patterns of employment in Ile-de-France, 1978-97", *Urban Studies* **43(11)**, 2075-2098.

[41] Hausman, J. A. (1978), "Specification tests in econometrics", *Econometrica* **46(6)**, 1251-1271.

[42] Islam, N. (1995), "Growth Empirics: A Panel Data Approach," *The Quarterly Journal of Economics* **110(4)**, 1127-1170.

[43] Kelejian, H. H., Murrell, P., and Shepotylo, O. (2013), "Spatial spillovers in the development of institutions," *Journal of Development Economics*, **101**, 297-315.

[44] LeSage, J. P., and Fischer, M. M. (2008), "Spatial growth regressions: model specification, estimation and interpretation," *Spatial Economic Analysis* **3(3)**, 275-304.

[45] LeSage, J., and Pace, R. K. (2009), *Introduction to Spatial Econometrics*, Chapman and Hall/CRC, Boca Raton, Florida.

[46] Lottmann, F. (2012), "Spatial dependencies in German matching functions," *Regional Science and Urban Economics*, **42(1-2)**, 27-41.

[47] Lundberg, J. (2006), "Using Spatial Econometrics to Analyse Local Growth in Sweden," *Regional Studies* **40(3)**, 303-316.

[48] Magalhães, A., Hewings, G. D., and Azzoni, C. R. (2005), "Spatial Dependence and Regional Convergence in Brazil," *Investigaciones Regionales* **6**, 5-20.

[49] Mankiw, N. G., Romer, D., and Weil, D. N. (1992), "A Contribution to the Empirics of Economic Growth," *The Quarterly Journal of Economics* **107(2)**, 407-437.

[50] Martin, P., and Ottaviano, G. I. (2001), "Growth and agglomeration," *International Economic Review*, **42(4)**, 947-968.

[51] Millo, G., and Piras, G. (2012), "splm: Spatial Panel Data Models in R," *Journal of Statistical Software* **47(1)**, 1-38.

[52] Monfort, P. (2008), *Convergence of EU Regions: Measures and Evolution.* Brussels: European Commission, Regional Policy.

[53] Moran, P. A. (1950), "Notes on continuous stochastic phenomena," *Biometrika* **37(1/2)**, 17-23.

[54] Moreno Serrano, R., and Vayá Valcarce, E. (2002), "Econometría Espacial: Nuevas Técnicas para el Análisis Regional. Una Aplicación a las Regiones Europeas," *Investigaciones Regionales* **1**, 83-106.

[55] Mutl, J., and Pfaffermayr, M. (2011), "The Hausman test in a Cliff and Ord panel model," *The Econometrics Journal* **14(1)**, 48-76.

[56] Nagaraj, R., Varoudakis, A., and Véganzonès, M.-A. (2000), "Long-Run Growth Trends and Convergence across Indian States," *Journal of International Development* **12(1)**, 45-70.

[57] National Institute of Statistics and Information (2017), Perú: Indicador de la Actividad Productiva Departamental 2017. Lima, Perú. Technical Report.

[58] Pfaffermayr, M. (2012), "Spatial Convergence of Regions Revisited: A Spatial Maximum Likelihood Panel Approach," *Journal of Regional Science* **52(5)**, 857-873.

[59] Phillips, P. C. B., and Sul, D. (2009), Economic Transition and Growth. *Journal of Applied Econometrics* **24(7)**, 1153-1185.

[60] Quah, D. (1993), "Empirical Cross-Section Dynamics in Economic Growth," *European Economic Review* **37**, 426-434.

[61] Rey, S. J., and Montouri, B. D. (1999), "US Regional Income Convergence: A Spatial Econometric Perspective," *Regional Studies* **33(2)**, 143-156.

[62] Sutton, M. B., Lindow, G., Serra, M. I., Ramirez, G., and Pazmino, M. F. (2006), "Regional Convergence in Latin America," International Monetary Fund Working Paper **06/125**.

[63] Williamson, J. G. (1965), "Regional Inequality and the Process of National Development: A Description of the Patterns," *Economic Development and Cultural Change* **13(4)**, 1-84.

[64] Wooldridge, J. M. (2015). *Introductory Econometrics: A Modern Approach.* Nelson Education, Toronto, Ontario.

[65] Ying, L. G. (2000), "Measuring the spillover effects: Some Chinese evidence," *Papers in Regional Science*, **79(1)**, 75-89.

Table 1. Descriptive Statistics for Variables, 1979-2017

Variable	Mean	Std. dev.	Min	Max	Obs
Gross Domestic Product per capita	9429.826	7996.029	2317.332	52637.82	936
Share of agriculture in the region	0.121	0.073	0.015	0.385	936
Share of industry in the region	0.416	0.199	0.079	0.869	936
Share of services in the region	0.390	0.158	0.078	0.764	936
Share of construction in the region	0.073	0.058	0.007	0.499	936
Regional population density	31.035	46.658	0.388	321.298	936
Specialization coefficient	0.212	0.121	0.012	0.511	936

Data Source: National Institute of Statistics and Information (INEI), 1979-2017.

Table 2. Global Moran I Statistic for Regional per Capita GDP

Year	Moran's I value	Standard Deviation	p-value	Year	Moran's I value	Standard Deviation	p-value
1979	0.094	0.091	0.078	1999	0.127	0.098	0.054
1980	0.120	0.104	0.071	2000	0.134	0.098	0.050
1981	0.103	0.102	0.086	2001	0.127	0.099	0.053
1982	0.128	0.100	0.049	2002	0.112	0.094	0.064
1983	0.131	0.104	0.052	2003	0.114	0.090	0.054
1984	0.119	0.099	0.058	2004	0.112	0.089	0.052
1985	0.140	0.093	0.035	2005	0.106	0.087	0.060
1986	0.123	0.101	0.058	2006	0.105	0.092	0.064
1987	0.120	0.106	0.072	2007	0.111	0.100	0.073
1988	0.099	0.114	0.115	2008	0.090	0.092	0.093
1989	0.111	0.097	0.066	2009	0.077	0.093	0.113
1990	0.083	0.107	0.129	2010	0.091	0.096	0.097
1991	0.120	0.096	0.050	2011	0.095	0.106	0.113
1992	0.120	0.093	0.046	2012	0.099	0.104	0.101
1993	0.095	0.096	0.087	2013	0.090	0.102	0.114
1994	0.096	0.096	0.088	2014	0.105	0.103	0.090
1995	0.109	0.104	0.085	2015	0.113	0.104	0.083
1996	0.119	0.101	0.063	2016	0.160	0.111	0.049
1997	0.119	0.097	0.052	2017	0.176	0.112	0.037
1998	0.129	0.101	0.053				

Data Source: National Institute of Statistics and Information (INEI), 1979-2017.

Table 3. Summary of Local Measures of Spatial Association: GDP per Capita 1979-2017

Regions	HH	HL	LL	LH
Amazonas				$2016-2017$
Áncash				
Apurímac				
Arequipa				
Ayacucho				
Cajamarca				$1979; 1980; 1982; 1983; 1998-2000$
Cusco				
Huancavelica				
Huánuco				
Ica				
Junín				
La Libertad				$1979-2000, 2014-2017$
Lambayeque				
Lima				
Loreto		$1981; 1982, 1985-1987$		$1988-2017$
Madre de Dios				
Moquegua				
Pasco				
Piura				
Puno			$1979-2017$	
San Martín				$2015; 2017$
Tacna				
Tumbes				
Ucayali				
Moran Global	$1979-1987, 1989, 1991-2008, 2010, 2014-2017$			

Notes: Years local statistic is significant at 1%. HH, years local statistic is in quadrant 1 of Moran's scatterplot; HL, years local statistic is in quadrant 2 of Moran's scatterplot; LL, years local statistic is in quadrant 3 of Moran's scatterplot; LH, years local statistic is in quadrant 4 of Moran's scatterplot.

Table 4. Estimation results of Convergence Model without Spatial Interaction Effects

	Pooling OLS (1)	Region-Fixed Effects (2)	Time-Fixed Effects (3)	Two-Way Fixed Effects (4)
β	-0.016^a	-0.133^a	-0.016^a	-0.208^a
	(0.004)	(0.016)	(0.004)	(0.017)
Share of agriculture	0.160^b	0.205^a	0.218^a	0.484^a
in the region	(0.066)	(0.079)	(0.069)	(0.086)
Share of industry	0.113^b	0.240^a	0.150	0.353^a
in the region	(0.049)	(0.072)	(0.051)	(0.072)
Share of service	0.062	0.004	0.096^c	-0.101
in the region	(0.054)	(0.083)	(0.056)	(0.086)
Log of Regional	0.006^a	0.014	0.007^a	-0.166^a
population density	(0.002)	(0.013)	(0.002)	(0.029)
Specialization coefficient	0.053	0.148^b	0.058^c	0.165^a
	(0.034)	(0.063)	(0.034)	(0.062)
Fixed effects by year	No	No	Yes	Yes
Fixed effects by region	No	Yes	No	Yes
Half-life	42.744	5.266	42.261	3.334
Observations	912	912	912	912
R^2	0.034	0.133	0.108	0.267
Log-likelihood	1127.108	1176.315	1163.450	1253.021
LR Test		$\chi^2_{(37)} = 153.41$	$\chi^2_{(23)} = 179.14$	$\chi^2_{(60)} = 251.83$
		$p - value = 0.000$	$p - value = 0.000$	$p - value = 0.000$
Hausman's specification tests				$\chi^2_{(6)} = 175.59$
				$p - value = 0.000$

Share of construction is omitted because of collinearity. Letters a, b, c denote statitical significance at 1%, 5% and 10%, respectively.

Table 5. Estimates Results using Spatial Panel Models with Fixed Effects.

	SEM (1)	SLM (2)	SARAR (3)	SDM (4)
β	-0.139^a	-0.133^a	-0.148^a	-0.182^a
	(0.015)	(0.015)	(0.036)	(0.016)
ρ		0.135^a	-0.378^b	0.170^a
		(0.050)	(0.179)	(0.050)
λ	0.193^a		0.494^a	
	(0.053)		(0.160)	
Share of agriculture	0.277^a	0.213^a	0.353^a	0.412^a
in the region	(0.082)	(0.078)	(0.129)	(0.083)
Share of industry	0.270^a	0.253^a	0.276^a	0.320^a
in the region	(0.071)	(0.070)	(0.101)	(0.070)
Share of services	0.025	0.020	0.011	-0.055
in the region	(0.081)	(0.081)	(0.125)	(0.080)
Log of Regional	0.004	0.017	-0.034	-0.114^a
population density	(0.014)	(0.012)	(0.036)	(0.026)
Specialization coefficient	0.156^b	0.150^b	0.165	0.157^a
	(0.061)	(0.062)	(0.131)	(0.060)
W $\times$ GDPpc				0.056^c
				(0.032)
W $\times$ Share of agriculture				-0.609^a
in the region				(0.121)
W $\times$ Share of industry				-0.134
in the region				(0.129)
W $\times$ Share of services				-0.042
in the region				(0.134)
W $\times$ Log of Regional				0.167^a
population density				(0.030)
W $\times$ Specialization coefficient				-0.093
				(0.138)
Half-life	4.985	5.201	4.690	3.815
N	912	912	912	912
R^2	0.022	0.024	0.012	0.002
Log-Likelihood	1182.812	1179.890	1187.206	1209
AIC	-2349.623	-2319.781	-2332.411	-2365.868
BIC	-2311.098	-2223.468	-2231.283	-2240.661
Hausman's specification test	$\chi^2_{(6)} = 97.534$	$\chi^2_{(6)} = 82.313$	$\chi^2_{(6)} = 112.89$	$\chi^2_{(13)} = 45.55$
	p-value= 0.000	p-value= 0.000	p-value= 0.000	p-value=0.000

Share of construction is omitted because of collinearity. Letters a, b, c denote statitical significance at 1%, 5% and 10%, respectively.

Tabla 6. Steady State according to the SDM

Regions	Value
Amazonas	-2.014^{b}
Áncash	0.213
Apurímac	-0.201
Arequipa	0.876
Ayacucho	-0.578
Cajamarca	-0.134
Cusco	-0.080
Huancavelica	0.478
Huánuco	-0.820
Ica	0.991
Junín	0.244
La Libertad	0.709
Lambayeque	0.677
Lima	2.500^{b}
Loreto	-1.381^{c}
Madre de Dios	-1.977^{b}
Moquegua	1.933^{b}
Pasco	-0.339
Piura	-0.224
Puno	-0.591
San Martín	-1.168
Tacna	1.194
Tumbes	0.816
Ucayali	-1.347

Letters a, b, c denote statitical significance at 1%, 5% and 10%, respectively.

Table 7. Clubs of Convergence

Panel A. Clubs of Convergence using Spatial Fixed Effects Model (SDM)	
Club 1	Lima, Moquegua
Club 2	Amazonas, Loreto, Madre de Dios
Club 3	Áncash, Arequipa, Ica, Junín, Lambayeque, La Libertad, Puno, Tacna, Tumbes
Club 4	Apurímac, Ayacucho, Cajamarca, Cusco, Huancavelica, Huánuco, Pasco, Piura, San Martín, Ucayali

Panel B. Clubs of Convergence by Delgado and Rodríguez (2015)	
Club 1	Áncash, Arequipa, Ayacucho, Cusco, Ica, La Libertad, Lima, Madre de Dios, Moquegua, Pasco, Tacna
Club 2	Amazonas, Cajamarca, Junín, Lambayeque, Piura
Club 3	Huancavelica, Loreto, Puno, San Martín, Tumbes
Club 4	Apurímac, Huánuco

Table 8. Results from Estimations of Impact Measures

Variable	Direct Effect	Indirect Effect	Total Effect
β	-0.181^a	0.030	-0.150^a
	(0.017)	(0.039)	(0.044)
Share of agriculture	0.396^a	-0.639^a	-0.243^c
in the region	(0.079)	(0.136)	(0.141)
Share of industry	0.323^a	-0.083	0.239
in the region	(0.067)	(0.145)	(0.160)
Share of service	-0.051	-0.047	-0.098
in the region	(0.080)	(0.153)	(0.173)
Log of Regional	-0.109^a	0.174^a	0.065^a
population density	(0.026)	(0.031)	(0.024)
Specialization coefficient	0.159^a	-0.070	0.088
	(0.060)	(0.160)	(0.175)

Share of construction is omitted because of collinearity. Letters a, b, c denote statitical significance at 1%, 5% and 10%, respectively.

Figure 1. Annual Peruvian per Capita GDP, 1979-2017 (Soles, at 2007 constant value). Data source: National Institute of Statistics and Information (INEI), 1979–2017.

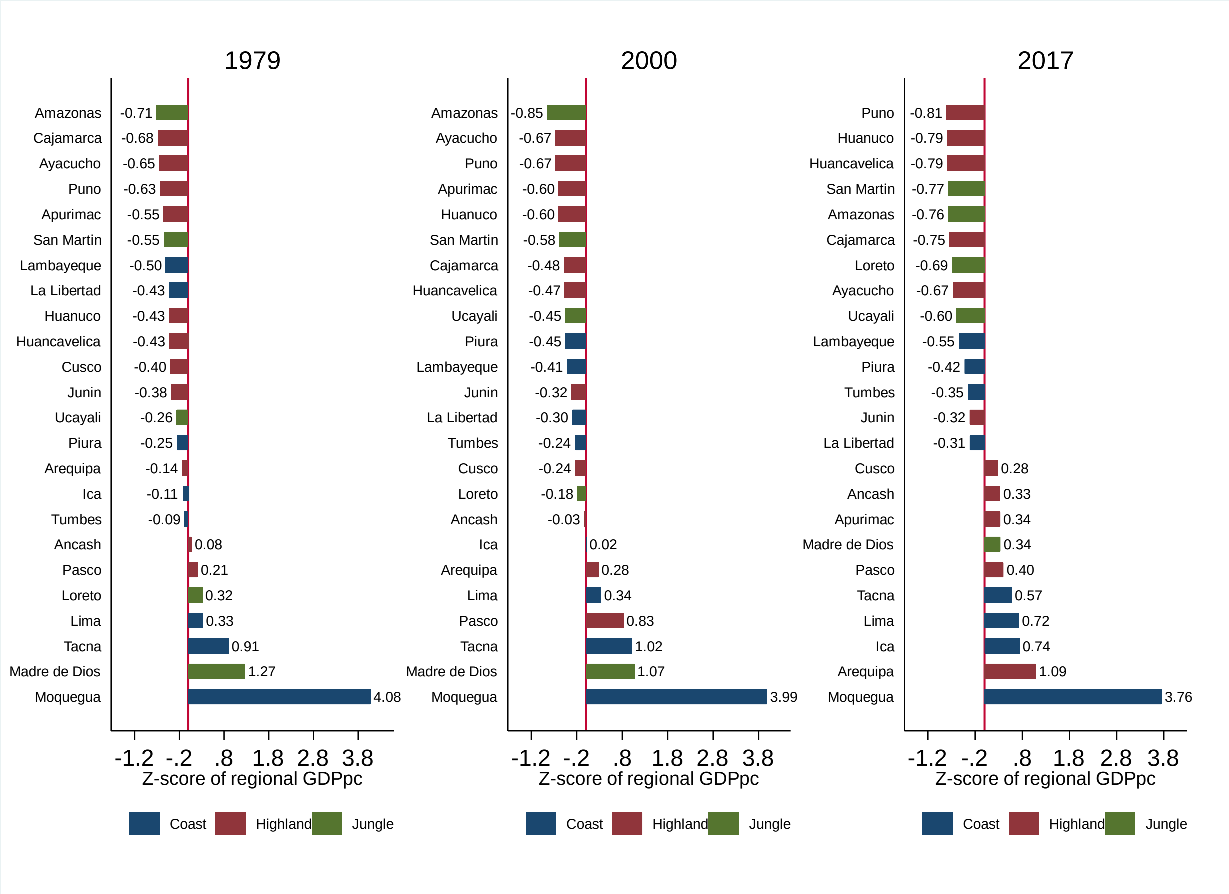

Figure 2. Z-scores for Regional per Capita GDP in 1979, 2000 and 2017.
Data Source: National Institute of Statistics and Information (INEI), 1979–2017.

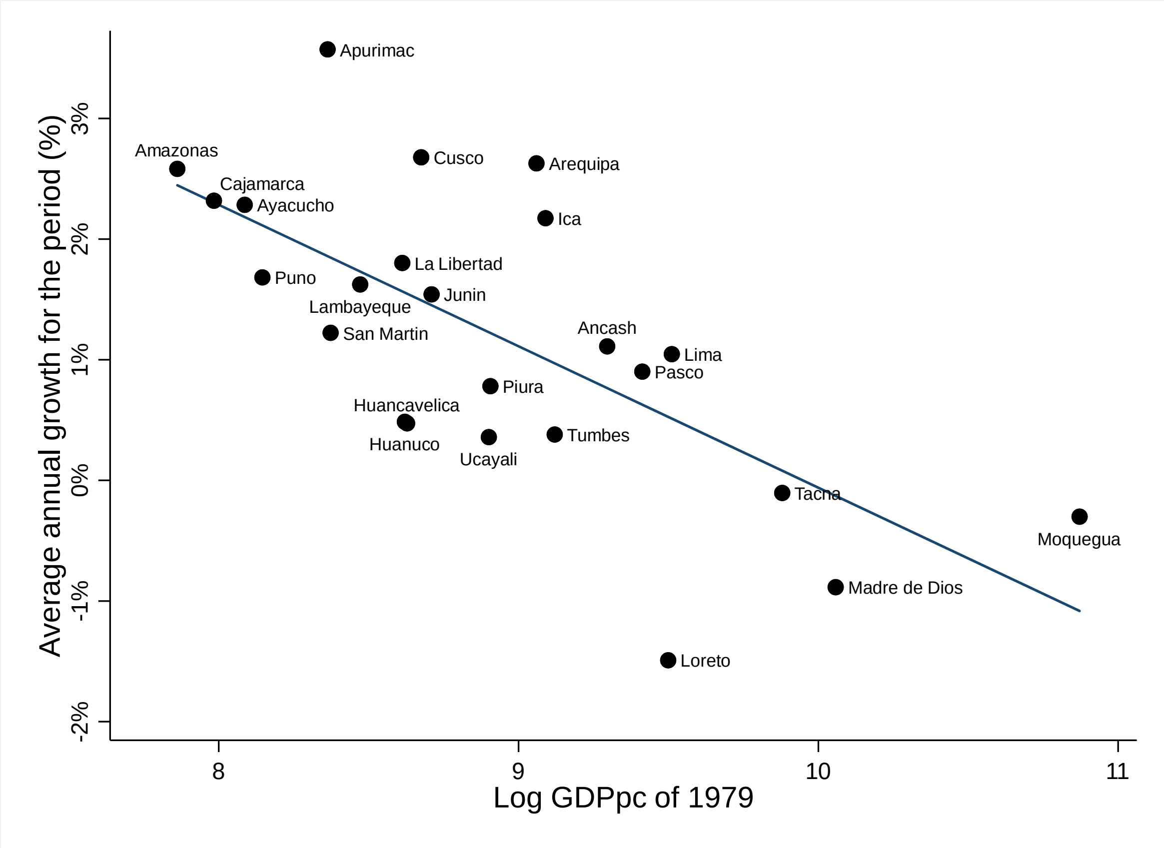

Figure 3. Relation between per Capita GDP in the Initial Period and Annual Growth Rate by Region, 1979-2017.
Data Source: National Institute of Statistics and Information (INEI), 1979–2017.

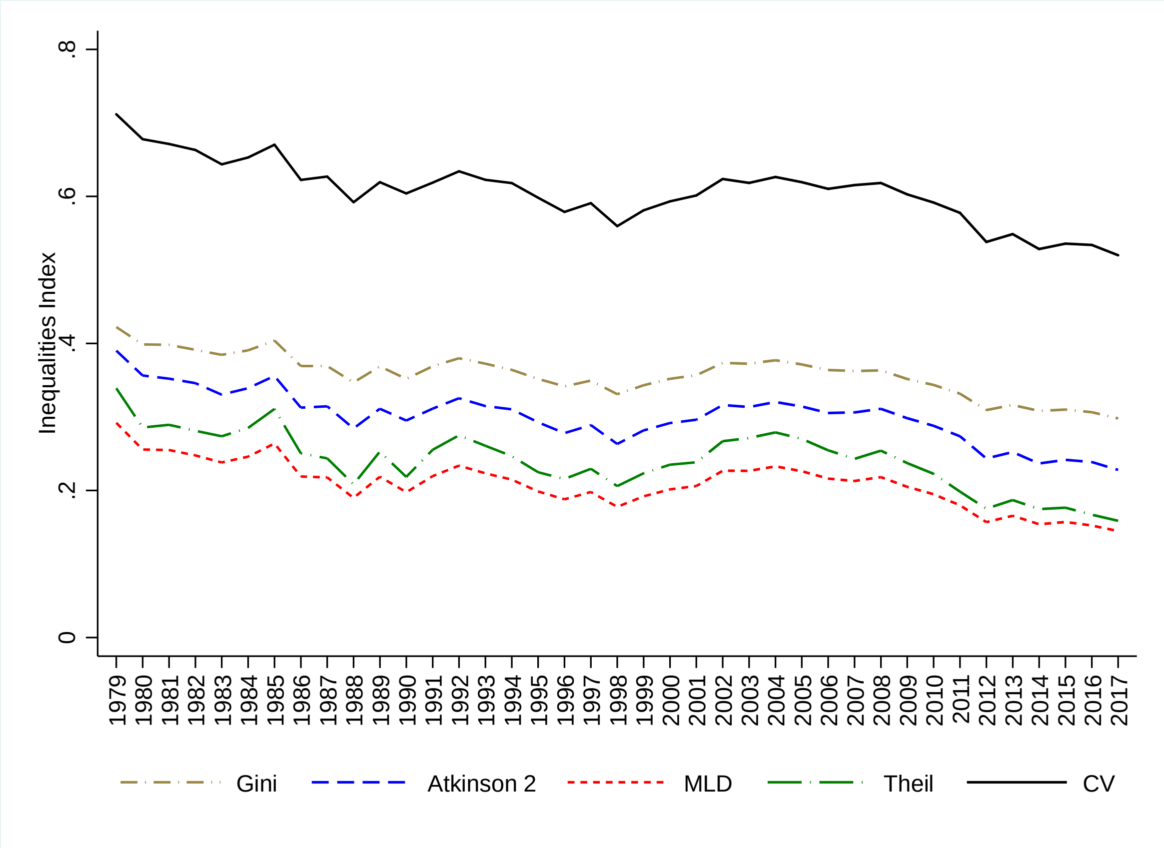

Figure 4. Regional per Capita GDP Inequalities in Peru between 1979 and 2017. Data Source: National Institute of Statistics and Information (INEI) 1979–2017.

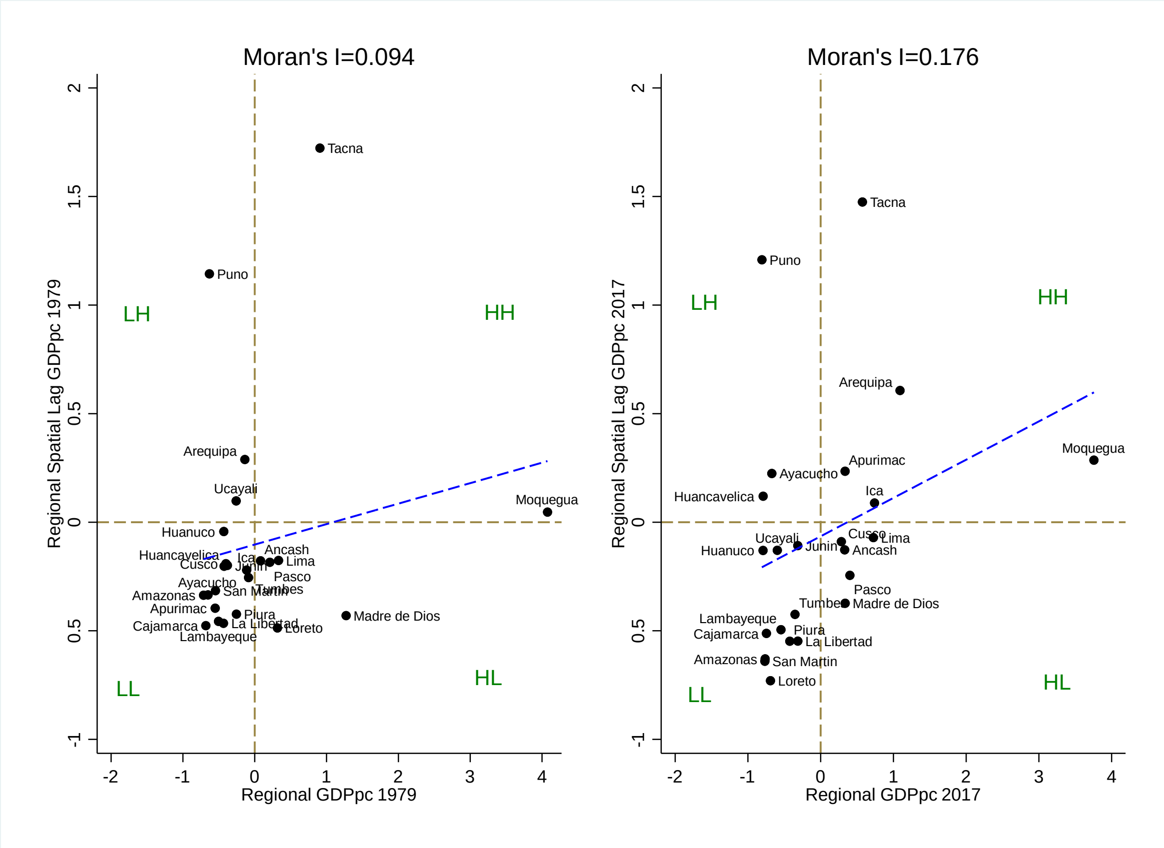

Figure 5. Moran Scatter Plots using Regional Annual per Capita GDP in 1979 and 2017. Data source: National Institute of Statistics and Information (INEI), 1979–2017.

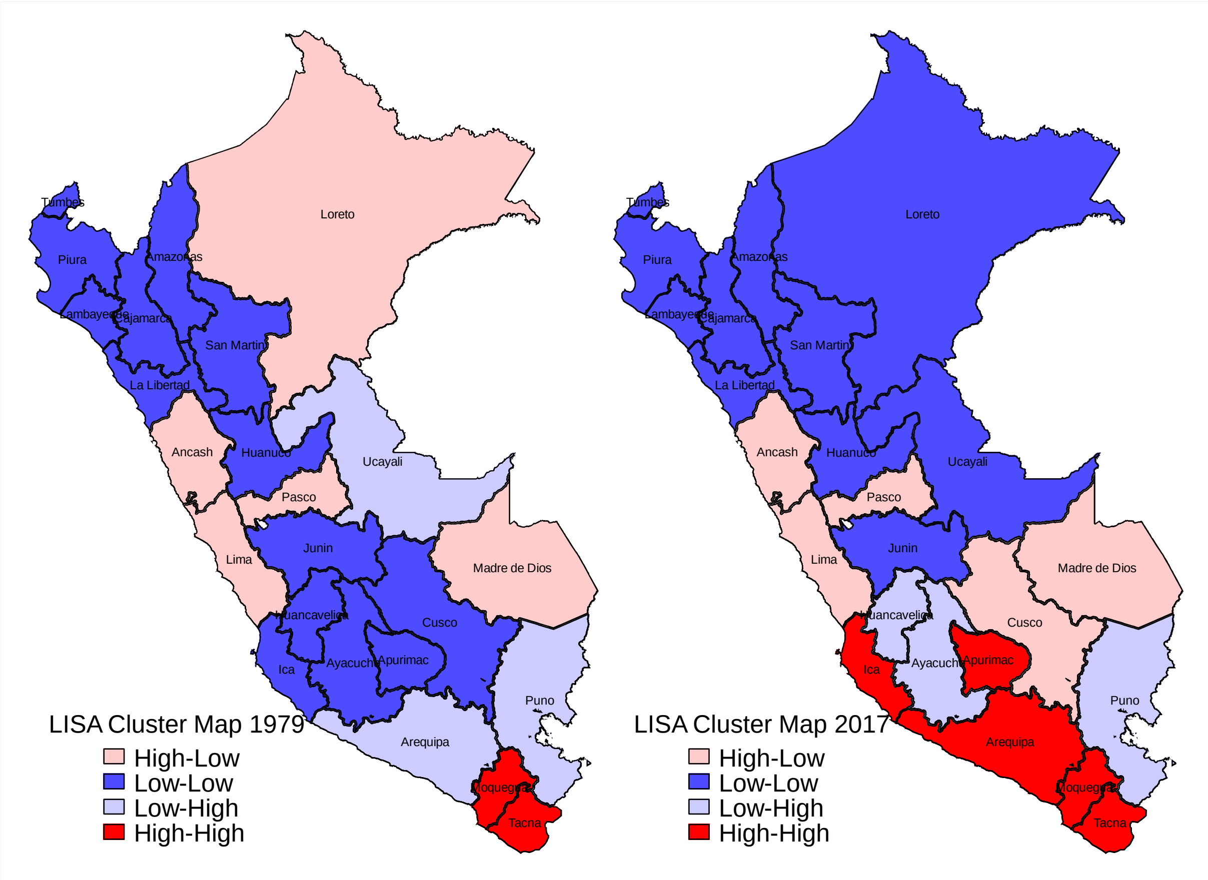

Figure 6. Peruvian Maps indicating Positions of Points in Moran Scatter Plots in 1979 (left) and 2017 (right).
Data Source: National Institute of Statistics and Information (INEI), 1979–2017.

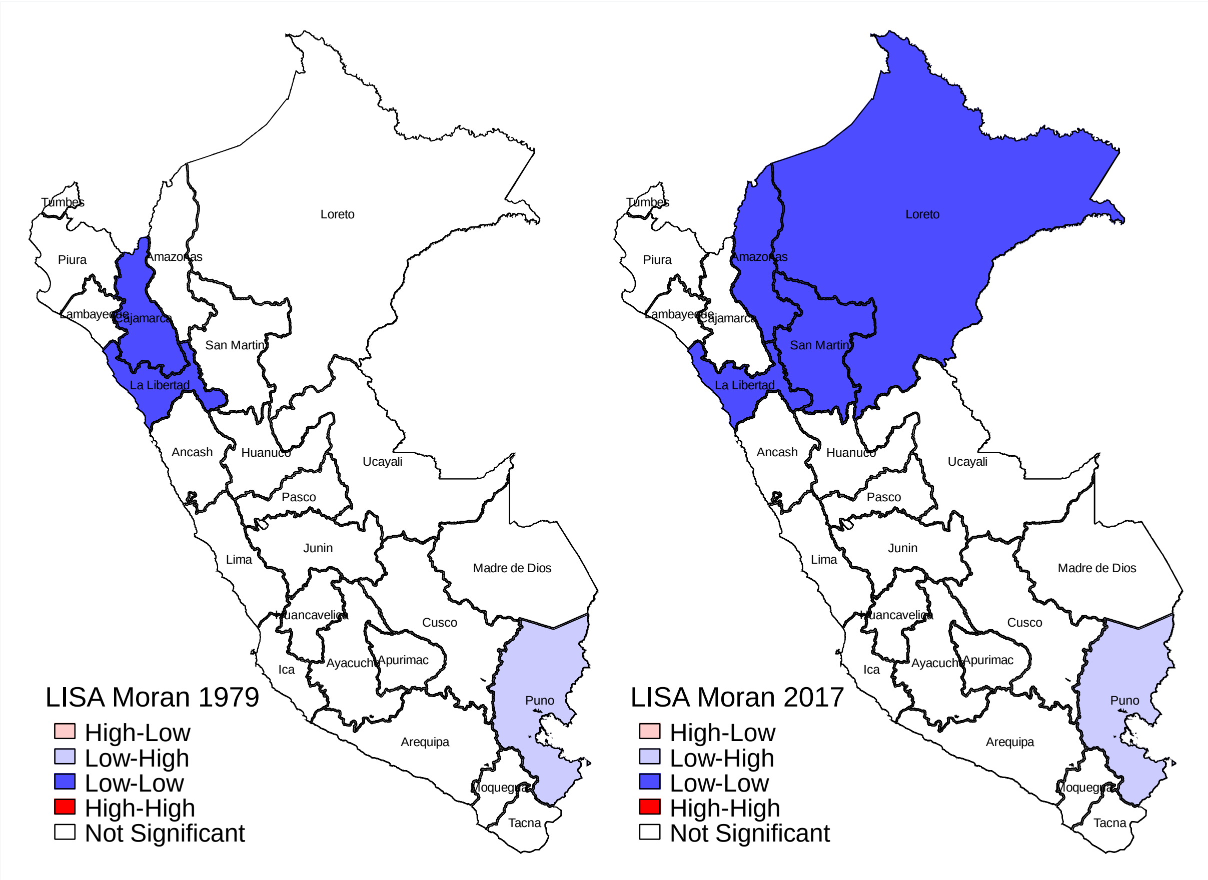

Figure 7. Moran Significance Maps for Regional per Capita GDP in Peru in 1979 (left) and 2017 (right).
Data Source: National Institute of Statistics and Information (INEI), 1979–2017.

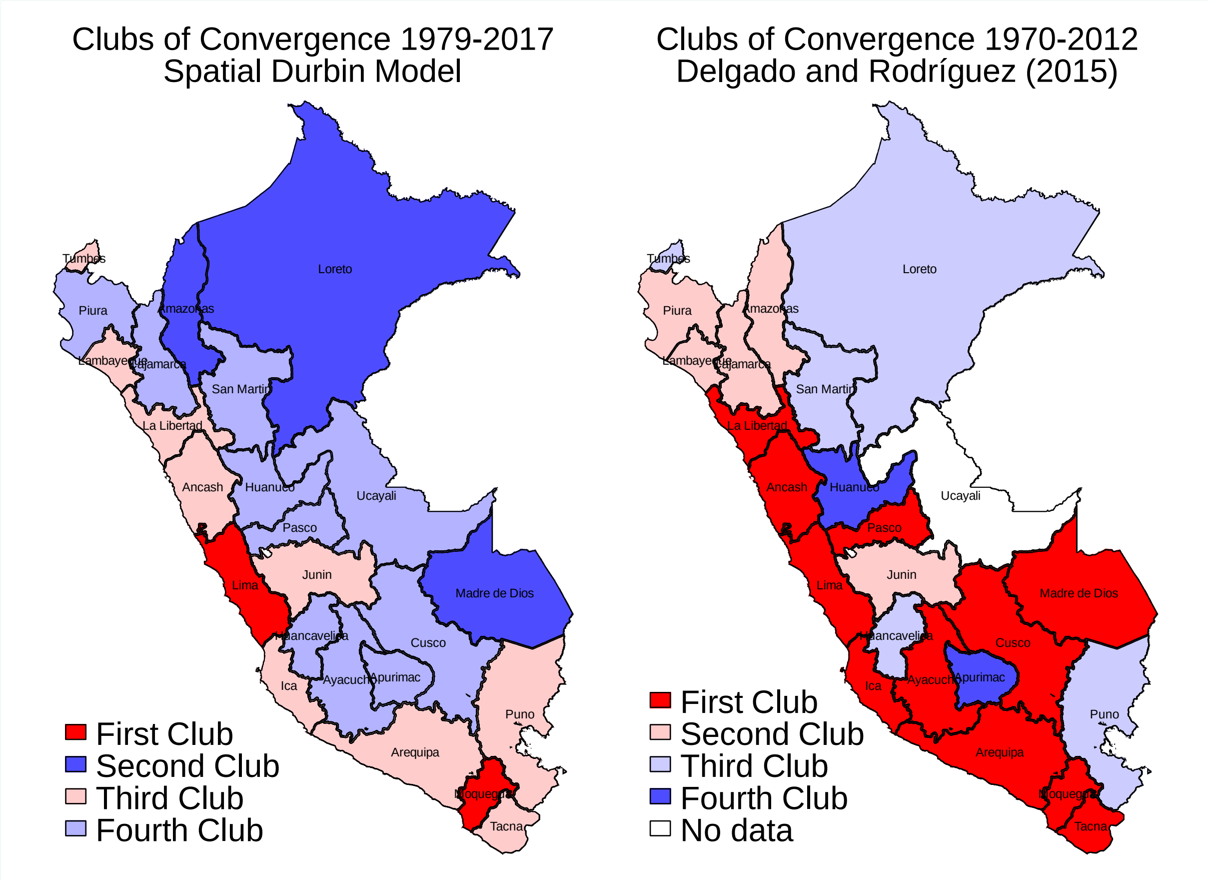

Figure 8. Maps of Convergence Clubs
Data Source: National Institute of Statistics and Information (INEI), 1979–2017.

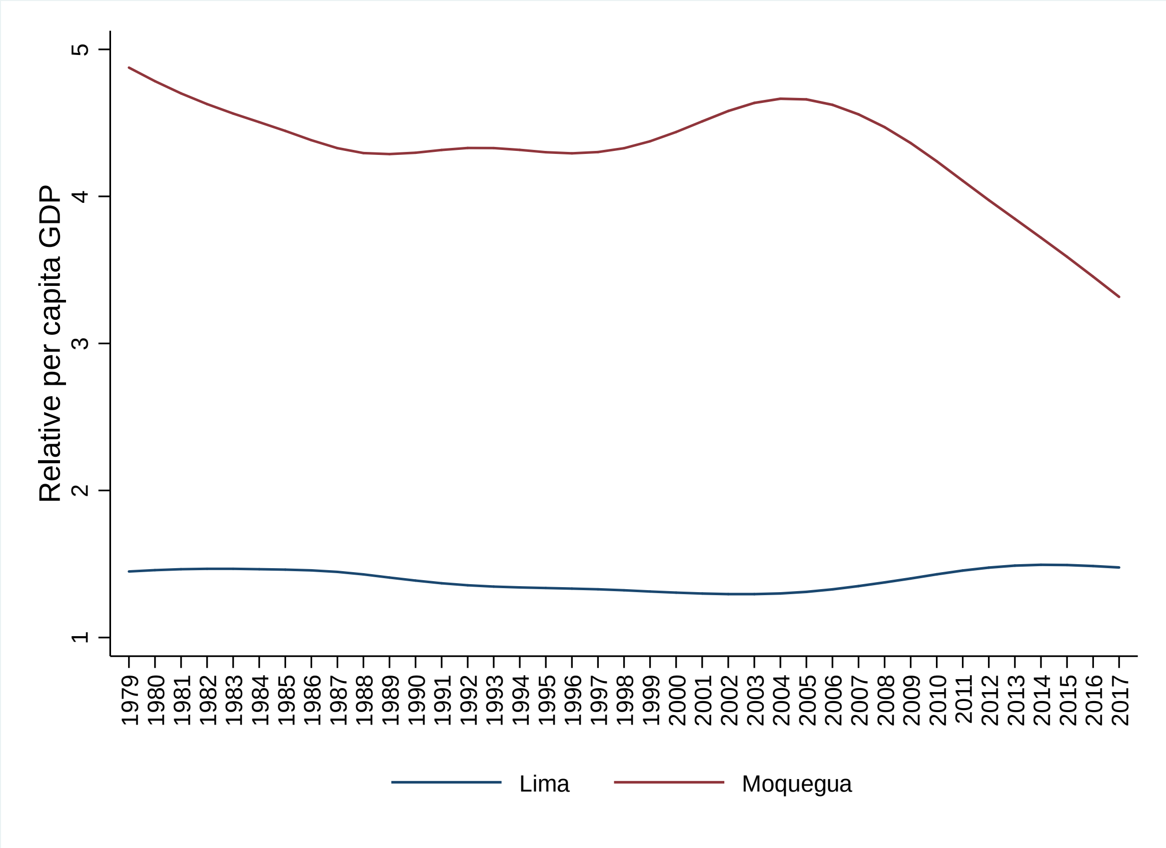

Figure 9a. First Club of Convergence - Regional per capita GDP.

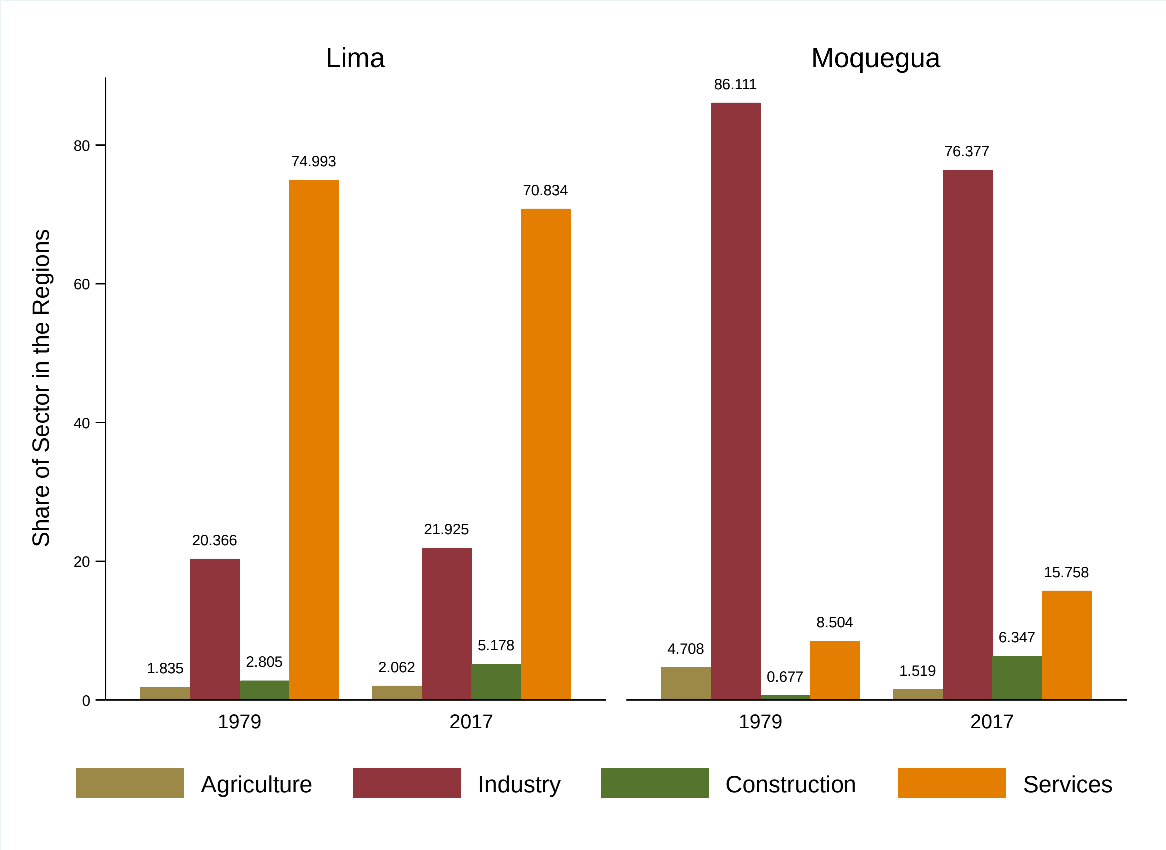

Figure 9b. First Club of Convergence - Share of Sectors in the Regions.

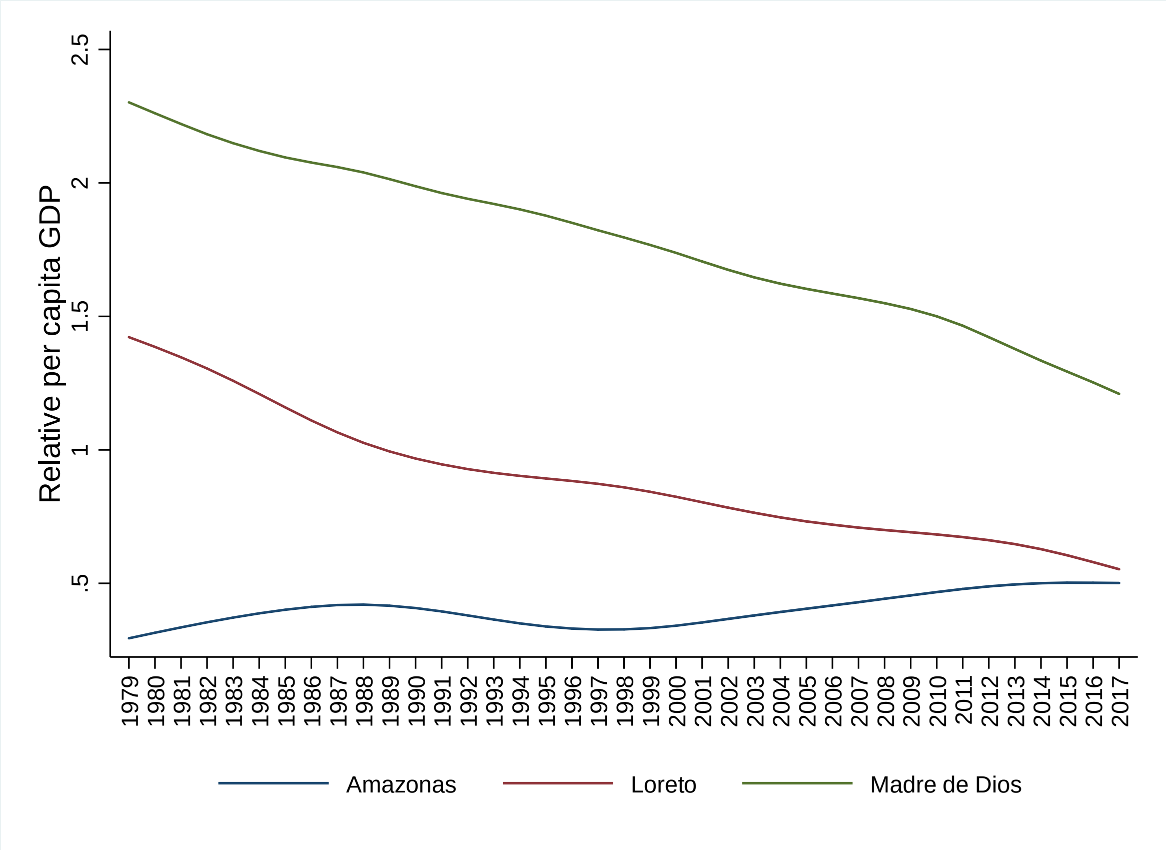

Figure 10a. Second Club of Convergence - Regional per capita GDP.

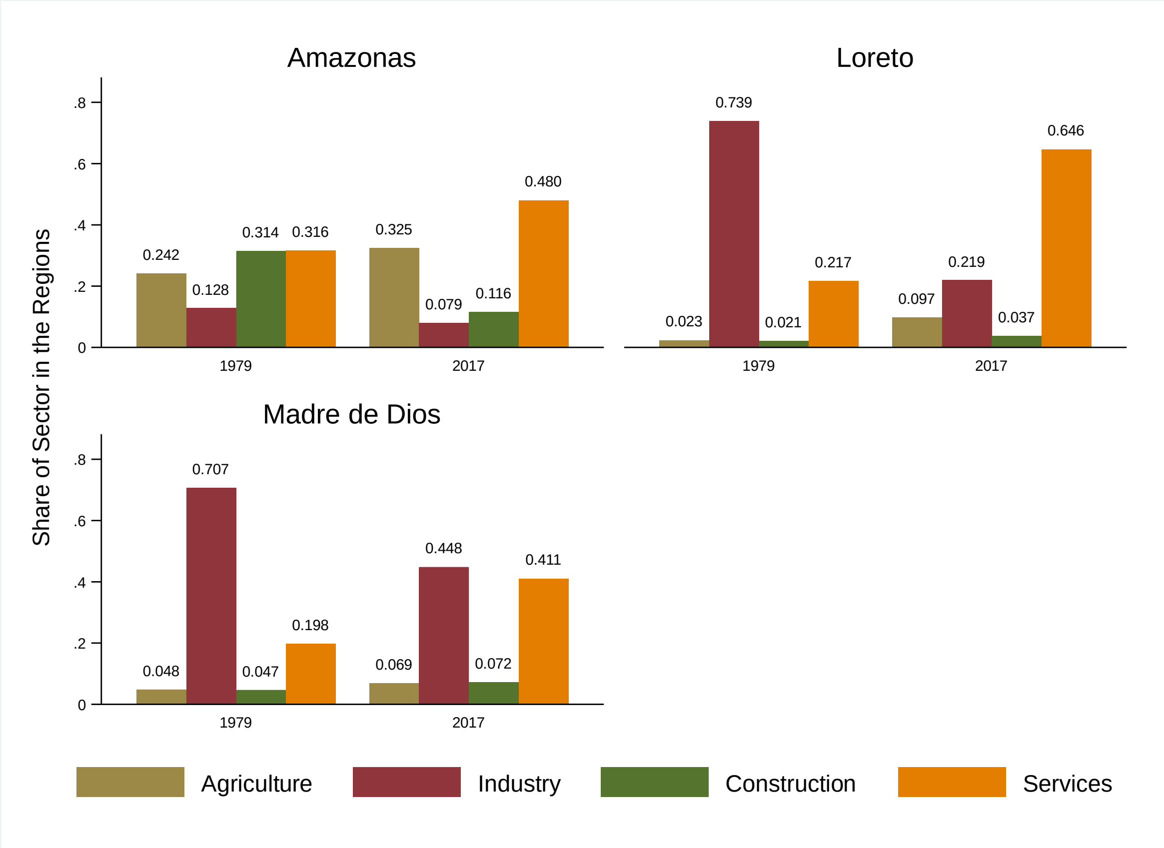

Figure 10b. Second Club of Convergence - Share of Sectors in the Regions.

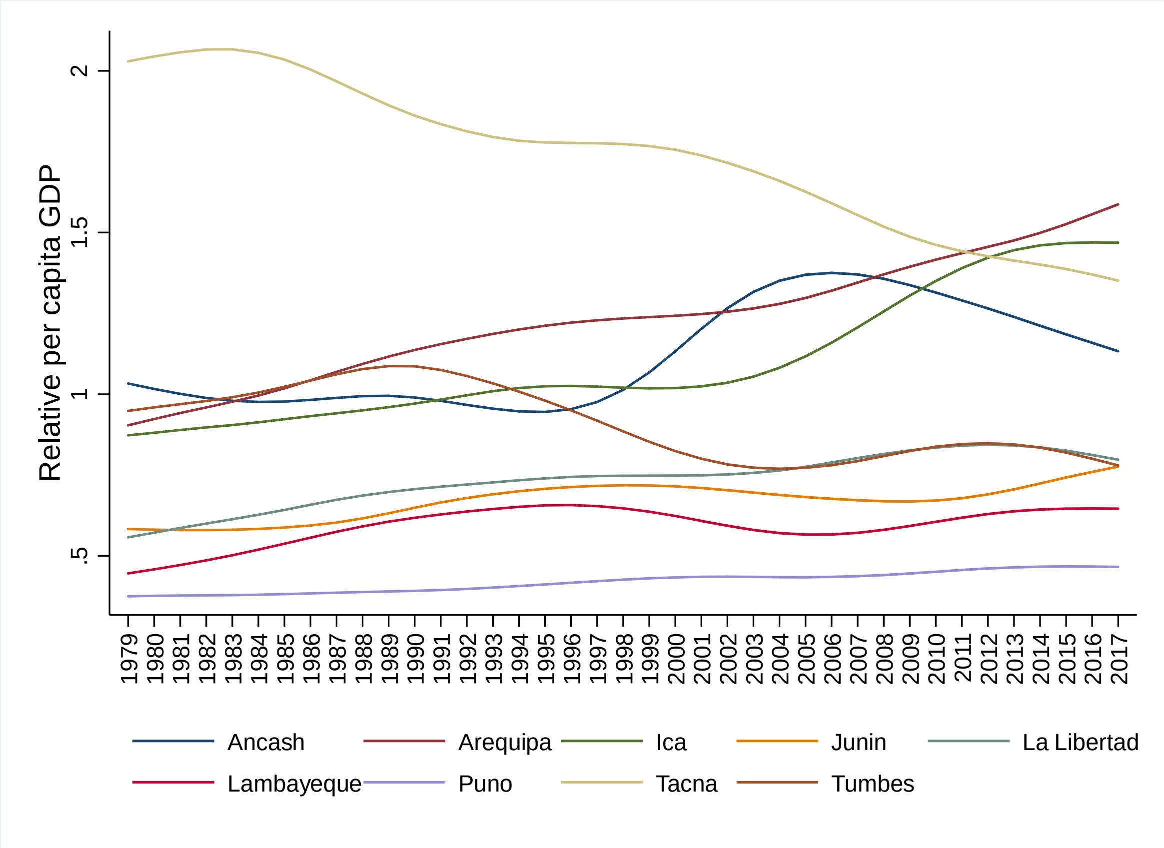

Figure 11a. Third Club of Convergence - Regional per capita GDP.

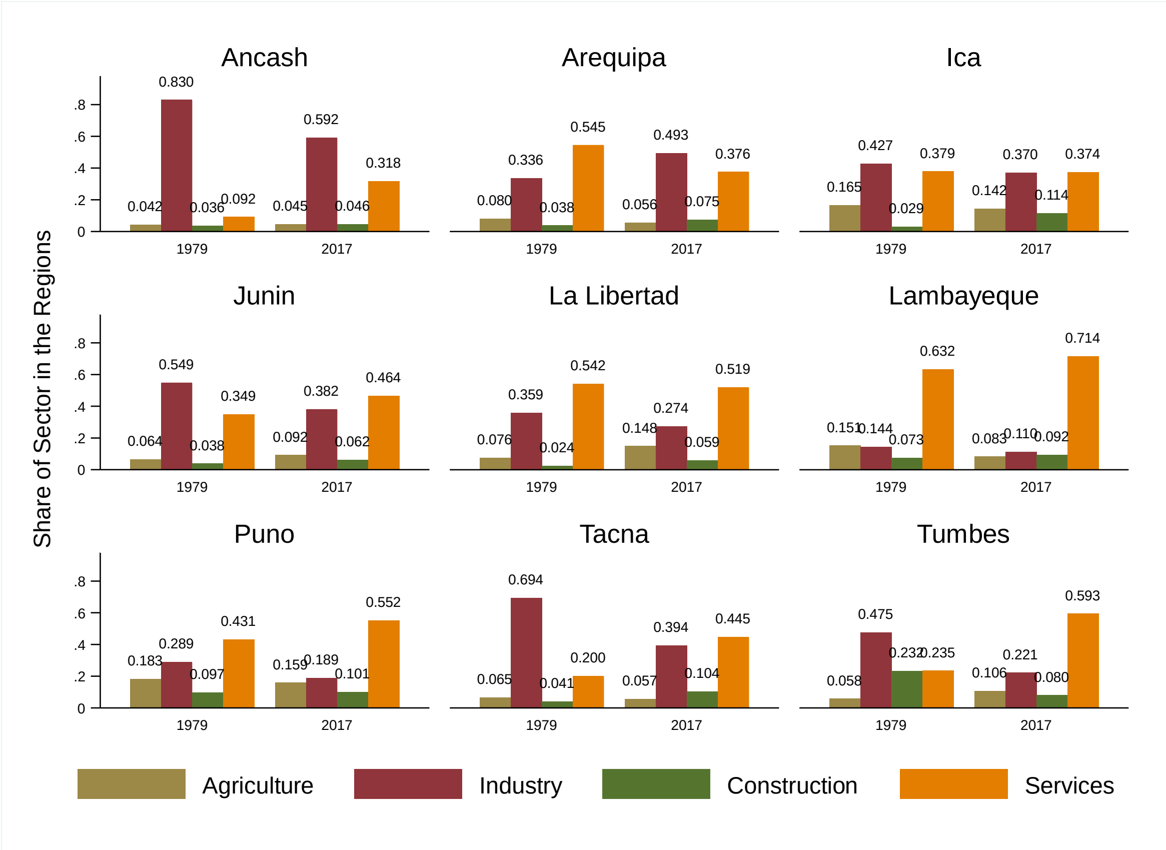

Figure 11b. Third Club of Convergence - Share of Sectors in the Regions.

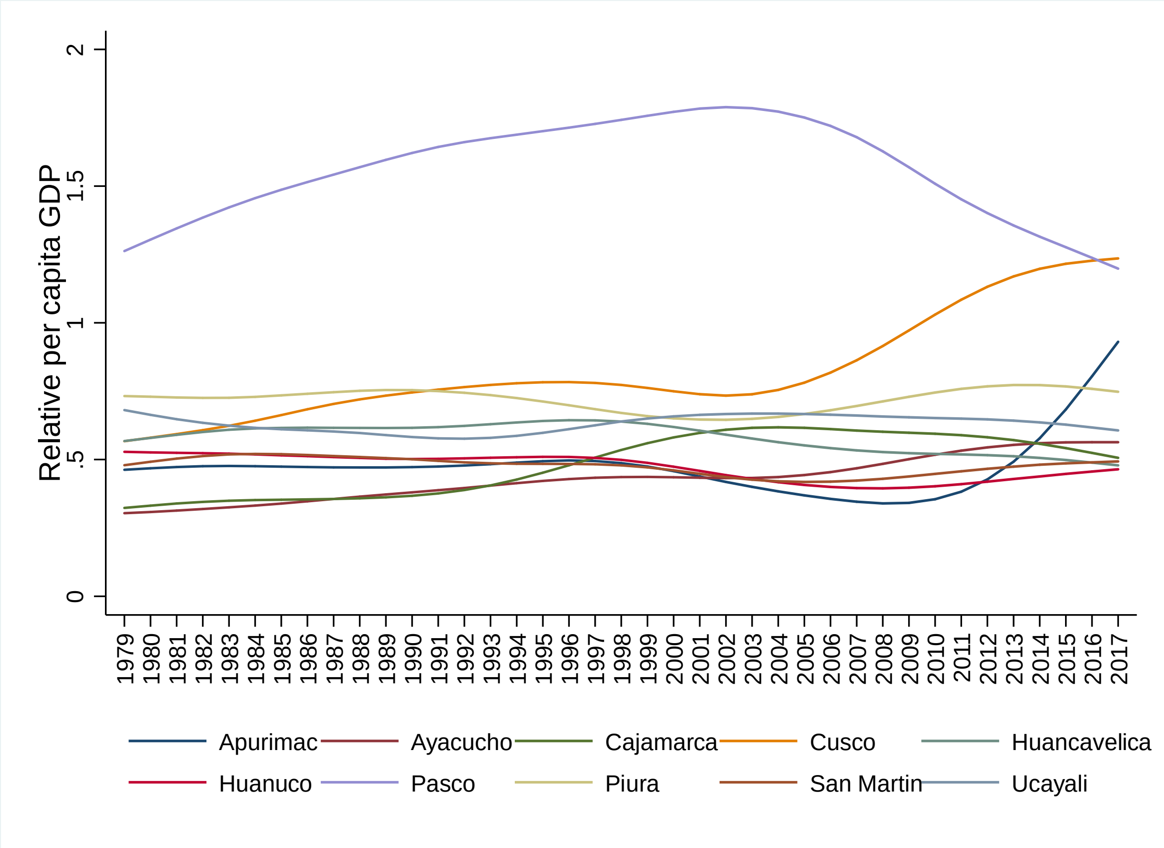

Figure 12a. Fourth Club of Convergence - Regional per capita GDP.

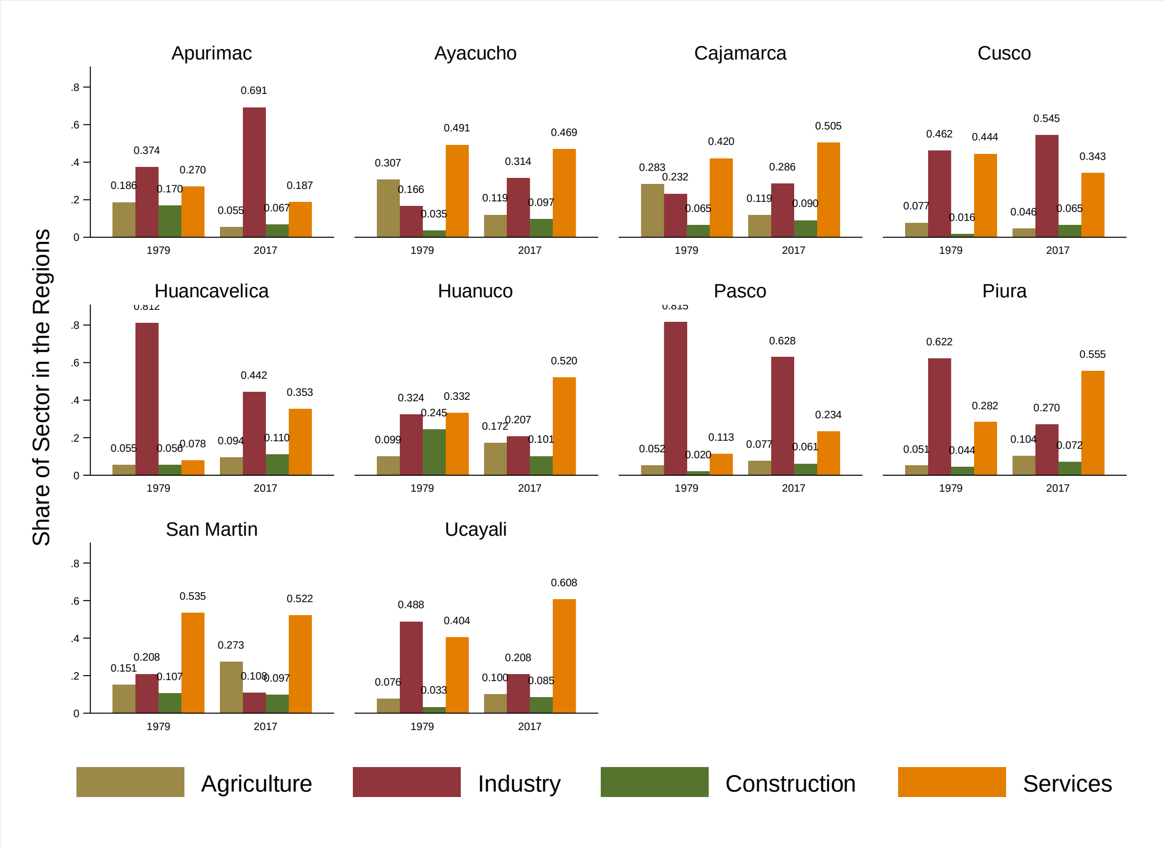

Figure 12b. Fourth Club of Convergence - Share of Sectors in the Regions.

ÚLTIMAS PUBLICACIONES DE LOS PROFESORES DEL DEPARTAMENTO DE ECONOMÍA

- *Libros*

José D. Gallardo Ku
2019 *Notas de teoría para para la incertidumbre*. Lima, Fondo Editorial de la Pontificia Universidad Católica del Perú.

Úrsula Aldana, Jhonatan Clausen, Angelo Cozzubo, Carolina Trivelli, Carlos Urrutia y Johanna Yancari
2018 *Desigualdad y pobreza en un contexto de crecimiento económico*. Lima, Instituto de Estudios Peruanos.

Séverine Deneulin, Jhonatan Clausen y Arelí Valencia (Eds.)
2018 *Introducción al enfoque de las capacidades: Aportes para el Desarrollo Humano en América Latina*. Flacso Argentina y Editorial Manantial. Fondo Editorial de la Pontificia Universidad Católica del Perú.

Mario Dammil, Oscar Dancourt y Roberto Frenkel (Eds.)
2018 *Dilemas de las políticas cambiarias y monetarias en América Latina*. Lima, Fondo Editorial de la Pontificia Universidad Católica del Perú.

María Teresa Oré e Ismael Muñoz (Eds.)
2018 *Aguas en disputa. Ica y Huancavelica, entre el entrampamiento y el diálogo*. Lima, Fondo Editorial de la Pontificia Universidad Católica del Perú.

Patricia Benavente, José Escaffi, José Távara y Alonso Segura
2017 *Las alianzas público-privadas (APP) en el Perú: Beneficios y riesgos*. Lima, Fondo Editorial de la Pontificia Universidad Católica del Perú.

Waldo Mendoza
2017 *Macroeconomía Intermedia para América Latina. Tercera edición actualizada y Aumentada*. Lima, Fondo Editorial de la Pontificia Universidad Católica del Perú.

César Guadalupe, Juan León, José S. Rodríguez y Silvana Vargas
2017 *Estado de la educación en el Perú, Análisis y perspectivas de la educación*. Lima. GRADE. Fortalecimiento de la Gestión Educativa en el Perú, FORGE.

Adolfo Figueroa
2017 *Economics of the Anthropocene Age*. Cham, Suiza, Palgrave Macmillan.

Adolfo Figueroa y Richard Web
2017 *Distribución del ingreso en el Perú. Lima, Instituto de Estudios Peruanos*.

Alfredo Dammert y Raúl García
2017 *Economía de la energía*. Lima, Fondo Editorial, Pontificia Universidad Católica del Perú.

- *Documentos de Trabajo*

No. 477 “The Mundell-Fleming Model: A dirty float versión.” Waldo Mendoza Bellido. Marzo, 2019.

No. 476 “Políticas de estabilización vs Políticas de crecimiento en Perú 2011-2018”. José A. Oscategui. Febrero, 2019.

No. 475 “El sector gastronómico en el Perú: encadenamientos y su potencial en crecimiento económico”. Mario D. Tello. Febrero, 2019.

No. 474 “Multiplicadores del turismo en el Perú, 2011”. Mario D. Tello. Febrero, 2019.

No. 473 “El sistema de Madrid y la reducción de los costos de transacción. Una evaluación econométrica”. José A. Tavera y Angelo Cozzubo. Febrero, 2019.

No. 472 “Oferta de trabajo del hogar remunerado en el Perú rural: 2015-2017”. Cecilia Garavito. Enero, 2019.

No. 471 “Impact of In-Kind Social Transfer Programs on the Labor Supply: a Gender Perspective”. Luis García y Erika Collantes. Diciembre, 2018.

No. 470 “Milking the Milkers: a Study on Buyer Power in the Dairy Market of Peru”. Tilsa Oré Mónago y José A. Tavera. Diciembre, 2018.

No. 469 “Gobernanza y regulación del sistema universitario peruano: luces y sombras de una nueva reforma”. José I. Távara. Diciembre, 2018.

No. 468 “Monetary and Fiscal History of Peru, 1960-2017: Radical Policy Experiments, Inflation and Stabilization”. Cesar Martinelli y Marco Vega. Diciembre, 2018.

No. 467 “The Role of Loan Supply Shocks in Pacific Alliance Countries: A TVP-VAR-SV Approach”. Carlos Guevara y Gabriel Rodríguez. Noviembre, 2018.

No. 466 “La apropiación de internet en adultos mayores: desafíos planteados por las economías informales en dos ciudades de América Latina”. Roxana Barrantes y Daniela Ugarte. Octubre, 2018.

No. 465 “¿Semillas mejoradas como escape de la pobreza? Evidencia cualitativa y cuantitativa para la sierra sur del Perú”. Victor Gamarra Echenique y Carmen Taipe Espinoza. Octubre, 2018.

No. 464 “Preferential Liberalization and Self-Enforcing Multilateral Cooperation: Evidence from Latin America’s Use of Tariffs, Antidumping and Safeguards”. Patricia Tovar. Agosto, 2018.

No. 463 “The determinants of private investment in a mining export economy. Peru: 1997-2017”. Waldo Mendoza Bellido y Erika Collantes Goicochea. Julio, 2018.

No. 462 “El espacio importa para el desarrollo humano: el caso peruano”. Efraín Gonzales de Olarte y Juan Manuel del Pozo. Junio, 2018.

No. 461 “El ecosistema digital y la economía regional peruana: heterogeneidad, dinámica y recomendaciones de política (2007- 2015)”. Roxana Barrantes y Paulo Matos. Mayo, 2018.

- *Materiales de Enseñanza*

No. 4 “Teoría de la Regulación”. Roxana Barrantes. Marzo, 2019.

No. 3 “Economía Pública”. Roxana Barrantes, Silvana Manrique y Carla Glave. Marzo, 2018.

No. 2 “Macroeconomía: Enfoques y modelos. Ejercicios resueltos”. Felix Jiménez. Marzo, 2016.

No. 1 “Introducción a la teoría del Equilibrio General”. Alejandro Lugon. Octubre, 2015.