Investigaciones Regionales – Journal of Regional Research
https://doi.org/10.38191/iirr-jorr.24.058

Accepted Article

Regional Economic Growth in Colombia: the role of Fiscal corruption and the Armed conflict

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Received: 19 September 2023
Accepted: 17 September 2024

Abstract:

This research explores the impact of armed violence and corruption on the economic growth of Colombia's departments from 1991 to 2017. Using models of spatial panels, statics and dynamics, we detect positive space-time indirect effects on departmental growth, including evidence of beta-convergence. Specifically, fiscal corruption exhibited a significant negative impact on short-term economic growth. Moreover, corruption primarily affected growth at the local level, with limited spillover effects observed from neighboring regions. Interestingly, our analysis did not yield statistically significant evidence regarding the impact of armed violence on economic growth.

Keywords: Economic growth; spatial dynamic model; fiscal corruption; armed conflict; beta convergence.
JEL Classification: O47; C23; D73; D74.

Crecimiento Económico Regional en Colombia: el rol de la corrupción fiscal y el conflicto armado

Resumen:

Esta investigación explora el impacto de la violencia armada y la corrupción en el crecimiento económico de los departamentos de Colombia desde 1991 hasta 2017. Usando modelos de paneles espaciales, estáticos y dinámicos, detectamos efectos indirectos espacio-temporales positivos en el crecimiento departamental, incluyendo evidencia de beta-convergencia. Específicamente, la corrupción fiscal tuvo un impacto negativo significativo en el crecimiento económico de corto plazo. Además, la corrupción afectó principalmente el crecimiento a nivel local, observándose efectos indirectos limitados desde las regiones vecinas. Cabe destacar que nuestro análisis no arrojó evidencia estadísticamente significativa sobre el impacto de la violencia armada en el crecimiento económico.

Palabras Clave: Crecimiento económico; modelo dinámico espacial; corrupción fiscal; conflicto armado; convergencia beta.
Clasificación JEL: O47; C23; D73; D74.

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1. Introduction

The concept of beta convergence stems from the neoclassical growth model, which predicts that economies with lower capital per worker will experience higher marginal returns on capital, leading to faster growth (Solow, 1956). This allows poorer economies to catch up with richer ones in terms of productivity and income per capita over time. Empirically, some studies have found evidence for conditional beta convergence, after controlling for factors like investments in human capital (Barro, 1991). However, corruption and armed conflict could frustrate this process of catch-up growth in developing countries.

Corruption harms economic growth in some key ways. Bribery leads bureaucrats to create complicated rules just to get more payments. This wastes resources. Corruption also means profits go to corrupt officials rather than legal owners. This removes the reward for productive investments that would boost growth (Mauro, 1995). Furthermore, corrupt states often have weak institutions and laws. This uncertainty deters investment (Aidt, 2003).

Armed conflict also severely disrupts economic activity. Violence directly destroys physical and human capital, critical for growth. Conflict areas see infrastructure damage, capital flight, and loss of skilled workers (Collier, 1999). Violence shifts public expenditure towards military spending, reducing investments in productivity-enhancing areas like infrastructure, education and healthcare (Knight et al., 1996). Similarly, armed conflict creates uncertainty, reducing investment in the same way that corruption does.

The negative effects of corruption and armed conflicts on economic growth can be attributed to different factors. First, corruption undermines the efficiency and effectiveness of public institutions, hindering the implementation of sound economic policies and inhibiting private sector development (Rose-Ackerman and Palifka, 2016). Second, armed conflicts disrupt infrastructure, hamper foreign investment, and displace human capital, leading to a decline in productivity and output (World Bank, 2011).

Furthermore, the consequences of corruption and armed conflicts extend beyond the immediate economic realm. They erode public trust, undermine social cohesion, and perpetuate inequality, creating a vicious cycle that perpetuates underdevelopment (Kaufmann et al., 2000). These interconnected issues highlight the urgency of addressing corruption and armed conflicts to foster sustainable economic growth and promote social well-being. Mueller (2021) estimates that conflict risk alone accounts for over half of the income divergence between countries with high and low propensity for armed conflict. Prolonged conflicts make it extremely difficult for poor states to catch up.

In summary, while beta convergence is expected theoretically, high corruption and armed violence appear to hinder income catch-up in practice. Understanding these relationships has important policy implications, both for growth theory and for promoting development in conflict-affected and fragile regions.

Colombia presents an interesting case study, facing challenges with both corruption and violence. Transparency International (2022) gives Colombia a low Corruption Perceptions Index1 score of 39/100, indicating high perceived corruption. Schwab (2018) ranked Colombia 66th globally in competitiveness, partly due to irregular payments and bribes. Regarding violence, Pinto-Borrego et al. (2005) estimated the direct and indirect costs of armed conflict from 1999-2003. Total costs reached 7.4% of GDP in 2003, mostly direct military and security costs. As a country afflicted by both high corruption and armed violence, Colombia offers a compelling case for examining how these factors may hinder economic growth.

[1] The Corruption Perceptions Index is an annual survey published by Transparency International that measures the perceived levels of public sector corruption in over 150 countries worldwide. The index uses a scale of 0 to 100, where 0 indicates the highest perceived level of corruption and 100 indicates the lowest perceived level. This index is based on expert assessments and opinion surveys, and is a widely recognized measure of corruption used extensively in academic research. For more information on this indicator, please visit https://www.transparency.org/en/

 ISSN: 1695-7253 e-ISSN: 2340-2717

The main objective of this paper is to explore the impact of armed violence and corruption on the process of economic growth and regional convergence among the departments of Colombia during the period 1991-2017. The specific objectives of the study are:

- To evaluate the existence of beta-convergence across the regions of Colombia, that is, whether the departments with lower levels of GDP per capita have experienced higher growth rates, which would allow them to catch up to the income levels of the richer departments.
- To determine the extent to which armed violence has influenced the process of economic growth and convergence among the Colombian departments. Previous evidence suggests that armed conflicts can frustrate the catching-up process of poorer economies, by distorting the efficient allocation of resources and generating uncertainty that discourages investment.
- To assess the impact of fiscal corruption on the process of economic growth and convergence across the Colombian departments. Corruption can also hinder the catching-up process by distorting the efficient allocation of resources.

To achieve these objectives, we model the Gross Domestic Product (GDP) per employed person at the regional level over the period 1991-2017, incorporating spatial spillover terms along with conflict and corruption as conditioning factors. The spatial models allow assessing convergence while accounting for potential spatial interactions and the hypothesized impacts of violence and corruption on income.

The paper is structured as follows. Section 2 presents the econometric models to be used, the extensions made from Spatial Econometrics. In Section 3, the main variables to be used are described, and an exploratory analysis during the period is carried-out. In Section 4, alternative spatial models are estimated, and the main results obtained are discussed. Finally, Section 5 summarizes the main conclusions of the research.

2. Regional convergence models and spatial effects

The seminal work of Baumol (1986), based on classical theory, stimulated the empirical study of the beta-convergence hypothesis, according to which the economic growth of a set of economies depends on their initial economic states. Under this hypothesis, a negative relationship between the growth rate and the initial state of an economy is expected, such that poorer economies grow more strongly than richer ones. In formal terms, Barro and Sala-i Martin (1992) suggest the following growth equation for a set of n economies:

$$\left(\frac{1}{T}\right) ln\left(\frac{y_{iT}}{y_{i0}}\right) = c + \beta ln(y_{i0}) + u_{iT}, \qquad i = 1, \dots, n, \tag{1}$$

where y_{iT} is the income per worker of the $i-th$ economy in period T, so that the cumulative average growth rate of the per-worker income of the $i-th$ economy between the initial period 0 and the final period T depends negatively ($\beta < 0$) on its initial state, y_{i0}; the parameter c that captures a common effect for all economies; and the error term u_{iT}. The coefficient β allows estimating the speed of convergence towards the steady state, i.e., the rate at which the economy approaches its long-term trajectory, and it is the one that gives rise to the name beta-convergence or beta-convergence.

The equation (1) is known as "absolute convergence" and has been widely contrasted for cross-sectional data (Barro and Sala-i Martin, 1992) using the Ordinary Least Squares (OLS) method. However, the empirical literature has not found consistent evidence with this result, largely due to the assumption of homogeneity among economies. Another limitation of equation (1) is the use of cross-sectional information that does not allow controlling for different unobservable factors. This inconvenience can be solved using panel data information.

Under the existence of heterogeneity among economies and using panel data (Islam, 1995), the convergence equation to be estimated can be expressed as:

$$\ln\left(\frac{y_{it}}{y_{it-1}}\right) = c_{0i} + c_{1t} + \beta \ln(y_{it-1}) + u_{it}, i = 1, \dots, n; t = 1, \dots, T, \tag{2}$$

where c_{0i} is a specific effect of the $i - th$ economy, and c_{1t} is a common temporal-specific effect for all economies. These effects can be considered fixed or random and are usually incorporated into a set of explanatory variables that represent "proxies" for different steady states in cross-sectional regressions. Traditionally, fixed effects are used since inference is restricted to the panel data sample. This panel data model is a version of the "conditional convergence" model, where a negative value of the coefficient β implies convergence of economies towards a steady state that is particular to each economy.

A limitation of traditional convergence analysis, whether in its absolute or conditional version, is the assumption that economies are independent of each other. Rey and Montouri (1999) argue that interdependence through spatial effects has a significant impact, altering conventional analysis. Omitting the influence of location in the growth process can produce biased and inconsistent results and, therefore, lead to erroneous conclusions.

The geographical interdependence between economies implies that the assumption of independence of the error vector u is not valid in equations (1) - (2). The existence of spatial dependence that has been ignored generates a specification error problem that can produce biased and/or inefficient estimates depending on the case, even leading to inconsistent estimates (Anselin, 1988).

To solve this limitation, Spatial Econometrics makes it possible to correct the mentioned specification problem. This field has developed specific methods to incorporate spatial effects into econometric models (Cliff and Ord, 1972; Anselin, 1988; LeSage and Pace, 2009; Elhorst, 2014, to name some relevant references). In the specific context of economic convergence, Abreu et al. (2005), Ertur et al. (2006), Arbia (2006) and Dall'Erba and Le Gallo (2008) can be mentioned.

The traditional approach of Spatial Econometrics incorporates spatial dependence through a spatial weights matrix W, of dimension n by n, where each element defines the neighbor relationship between economies, so that if an economy i is considered a neighbor of another economy j, then the element of W (or spatial weight), w_{ij} will be one, and if not, this value will be zero. The main diagonal of the matrix contains all zero elements (no region can be a neighbor of itself). The spatial weights matrix is usually row-standardized so that the sum of the weights in each row is equal to one.

A key point in this literature is to determine which observations are neighbors of each other. To do this, an interaction hypothesis must be established, which can be geographic, social, economic, or a combination of these types. Traditionally, geographic position has been used to determine the neighborhood (contiguity criterion, use of distance functions), although non-geographic alternatives are now common. Once W is defined, it is possible to specify spatial dependence by incorporating spatial lags of the dependent variable (Wy), the explanatory variables (WX), and the error term (Wu), or combinations of these lags, into the model. In the context of equation (2), in matrix format, and considering $\Delta\ln(y_t) = (\ln\left(\frac{y_{it}}{y_{it-1}}\right); \ i = 1, \dots, n)$, $y_t = (y_{it}; \ i = 1, \dots, n)$ $(n \times 1)$ with $\ln(y_{t-1})$ as part of the explanatory variable matrix X_t and omitting for simplicity the fixed effects $(c_0 + c_{1t})$, the most complex possible dependence model contains all three spatial terms simultaneously:

$$\begin{aligned} \Delta\ln(y_t) &= \rho W \Delta\ln(y_t) + X_t\beta + WX_t\theta + u_t, \\ u_t &= \lambda W u_t + \varepsilon_t, \qquad \text{for } t = 1, \dots, T, \end{aligned} \tag{3}$$

where $\varepsilon_t = (\varepsilon_{it}; i = 1, \dots, n)$ is a $(n \times 1)$ vector idiosyncratic errors $i.i.d.(0, \sigma_\varepsilon^2 I_n)$. The parameter ρ represents the endogenous spatial autocorrelation of neighborhood growth, the vector β $(K \times 1)$ captures the effects of the K explanatory variables, the vector θ $(K \times 1)$ captures the geographic or spillover effects of the explanatory variables, and λ measures the presence of a spatial lag in the error term. It is important to mention that the model in equation (3) specifies a global spatial dependence structure, in the sense that the parameters (ρ, θ, λ) are unique for the entire sample. Depending on the dimension of the cross-sectional sample size, n, this assumption of unique parameters can be relaxed by incorporating the possibility of including spatial heterogeneity among regions or sets of regions (models known as spatial regimes in the Spatial Econometrics literature).

The model (3) is not identified for the "reflection problem" (Manski, 1993), which means that there exists a linear combination of the model's parameters that produces the same predicted values of the model's variables, making it impossible to estimate those parameters uniquely (for more details about this problem in Spatial Econometrics see Elhorst, 2010a). The solution is to restrict the presence of spatial parameters, resulting in a significant variety of specifications. Among the most common, we can mention:

- SAR (Spatial AutoRegressive model)

$$\Delta \ln(y_t) = \rho W \Delta \ln(y_t) + X_t \beta + u_t, \qquad for\ \ t = 1, \dots, T \tag{4}$$

- SEM (Spatial Error Model)

$$\Delta \ln(y_t) = X_t \beta + u_t, \qquad u_t = \lambda W u_t + \varepsilon_t, \qquad for\ \ t = 1, \dots, T \tag{5}$$

- SARAR (Spatial AutoRegressive model with AutoRegressive disturbances)

$$\Delta \ln(y_t) = \rho W \Delta \ln(y_t) + X_t \beta + u_t, \qquad u_t = \lambda W u_t + \varepsilon_t, \ \ for\ \ t = 1, \dots, T \tag{6}$$

- SDM (Spatial Durbin Model)

$$\Delta \ln(y_t) = \rho W \Delta \ln(y_t) + X_t \beta + W X_t \theta + u_t, \qquad for\ \ t = 1, \dots, T \tag{7}$$

- SDEM (Spatial Durbin Error Model)

$$\Delta \ln(y_t) = X_t \beta + W X_t \theta + u_t, \qquad u_t = \lambda W u_t + \varepsilon_t, \quad for\ \ t = 1, \dots, T \tag{8}$$

Durbin models nest a simpler model under the assumption of no endogenous spatial autocorrelation ($\rho = 0$ for SDM) and spatial error incorrelation ($\lambda = 0$ for SDEM) known as SLX, where only explanatory variables contain spatial lags, WX_t.

Early empirical research on space and economic growth used ad hoc spatial effects without a theoretical convergence model. Model specification relied on data-driven techniques like spatial autocorrelation and heterogeneity for consistent estimates. An alternative approach is using a theory-driven model that derives a spatial model. Ertur and Koch (2007) extended the Solow (1956)'s neoclassical model by incorporating Arrow-Romer-type externalities and spatial externalities. This augmented beta convergence model, an SDM for cross-sections, was further expanded by Fischer (2011) to include additional control terms such as human capital and regional fixed effects for Europe (NUTS2). Recent extensions examine the model's applicability to regional data in China (Sun et al., 2017).

Yu and Lee (2012) researched an extension of Islam (1995)'s static panel data model to a dynamic approach (SDPD, Spatial Dynamic Panel Data) with fixed effects, allowing not only to control for omitted variable bias in the cross-section (individual and spatial effects) but also for omitted variable bias in the panel regression's temporal dynamics. The SDPD model is obtained by dynamizing a theoretical model similar to that proposed by Ertur and Koch (2007) and can be expressed as follows:

- SDPD model

$$\Delta \ln(y_t) = \rho W \Delta \ln(y_t) + \tau \Delta \ln(y_{t-1}) + \eta W \Delta \ln(y_{t-1}) + X_t \beta + u_t, \ \ for\ \ t = 2, \dots, T \tag{9}$$

where τ captures the temporal dynamics of the previous period in each economy $\Delta \ln(y_{t-1})$ and η captures the space-time component of period $t-1$, the impact of $W\Delta \ln(y_{t-1})$. The other elements have been previously defined. The model can be extended by incorporating spatial and temporal lags in the X matrix.

By introducing temporal dynamics, the condition $(\rho + \tau + \eta) < 1$ must be met for stationarity issues, and the restriction $(\eta = -\tau\rho)$ must also be met, such that the impact in time and space can be separated mathematically, avoiding over-identification problems (Elhorst, 2010b). By restricting the space-time coefficients of the SDPD model, similar specifications proposed by Anselin et al. (2008) can be obtained:

- Recursive model

$$\Delta\ln(y_t) = \rho W \Delta\ln(y_t) + \eta W \Delta\ln(y_{t-1}) + X_t\beta + u_t, \quad for\ t = 2, \dots, T \tag{10}$$

- Time-space simultaneous model:

$$\Delta\ln(y_t) = \rho W \Delta\ln(y_t) + \tau \Delta\ln(y_{t-1}) + X_t\beta + u_t, \qquad for\ t = 2, \dots, T \tag{11}$$

The estimation of these models can be carried out by Quasi Maximum Likelihood (QML) (Lee, 2004), by the Generalized Method of Moments (GMM) (Kelejian and Prucha, 1998, 1999) or by Bayesian methods (LeSage, 2014). In this research, the proposal by Lee (2004) and Yu and Lee (2012) based on QML will be used.

Among the empirical research on spatial effects for Colombia, Royuela and García (2015) and Galvis-Aponte and Hahn-De-Castro (2016) can be mentioned, who used a similar time period as proposed in this paper but with different approaches. Royuela and García (2015) analyze the convergence of different regional welfare indicators for a panel data in the period 1975-2005, confirming that there is convergence in Colombia in key social variables. Additionally, the presence of spatial autocorrelation reinforces convergence processes. Galvis-Aponte and Hahn-De-Castro (2016) analyze municipal economic growth in the period 1993-2012. The authors use a cross-sectional analysis where the results indicate that, under omission of spatial effects, there is evidence of convergence. However, this evidence disappears when these effects are incorporated into the model.

Another relevant study is carried out by Aristizábal and García (2021), who address economic growth and convergence in a spatial context. They estimate balanced panel models for 24 departments of Colombia for the period 2006-2016. The results of the spatial economic growth model estimates confirm departmental conditional convergence.

According to the literature review, there are no publications that use the spatial dynamic panel models.

3. Description of the database and exploratory analysis

Our approach is developed using a panel of data observed at the departmental level and with annual periodicity. The primary source of information is detailed in the Appendix A.

The analyzed variables are the follows:

- Dependent variable:

  $\Delta\ln(y_t)$: year-on-year difference in the natural logarithm of GDPpl (GDP divided by the labor force in each period).

- Explanatory variables:

  $\ln(y_{t-1})$: natural logarithm of GDPpl in period $t-1$.

  $\left(\frac{Victims}{Population}\right)_{t-1}$: rate of violence victims relative to the total population (per 100 inhabitants) by department in period $t-1$.

  $\left(\frac{Corruption}{GDP}\right)_{t-1}$: rate of economic amount from fiscal corruption (bribery) relative to departmental GDP in period $t-1$.

$\left(\frac{Damage}{GDP}\right)_{t-1}$: rate of economic amount of the damage caused by armed conflicts relative to GDP departmental GDP in period $t-1$.

In addition, we add control variables that are part of the usual specification in growth models: (1) $\ln\left(\frac{K}{GDP}\right)_t$: logarithm of the average public investment rate relative to departmental GDP in period t; (2) $\ln(gn)_t$: logarithm of the rate of growth of the labor force plus the annual rate of depreciation of physical capital, set at a value of 0.05 for all departments, as is customary in studies of economic growth.

Table 1 reports on the evolution of regional labor productivity in Colombia, represented by the gross domestic product obtained per worker over time, GDP per labor force (GDPpl). The results indicate that in 1991 there was a significant average of 17,187 (2015 dollars) produced per worker. However, the efficiency and quality of the workforce capital observed in the production process through GDPpl was diminished in 2017, with a registered decline of 0.81%. The previous regional results present a tendency to vary in 15,950 dollars in 1991, which also decreased to 5,403 in 2017. In relative terms, it can be observed that the regional GDPpl in the last year presented less deviation with respect to 1991, that is, the fluctuation of GDPpl trajectories decreased.

In general, it can be observed that high productivities are very distant from the low ones, but the historical trend shows that the high differences decreased over time. While in 1991, the highest GDPpl (66,410) was 14.6 times higher than the lowest (4,535), in 2017 the difference between the highest GDPpl (25,340) and the minimum (5,065) decreased to 5 times. That is, the maximum GDPpl in 1991 decreased by 3.28%, while the minimum GDPpl increased by 8.69%.

These results are a consequence of the economic evolution of the Colombian business sectors throughout this period. In the early 1990s, the agricultural sector and the manufacturing industry, considered important for Colombian development, faced difficulties due to scarce information and slow regulation of economic openness, which hindered job creation and affected GDPpl. Subsequently, the recession of 1999 led to increases in unemployment that revealed the financial fragility of the private sector. These situations were slowly overcome between 2010 and 2014 (Ocampo and Romero, 2015). In these years, growth was sustained but not to the expected magnitude. Initially, Colombia benefited from the currency generated by the regional mining and energy exploitation. However, the fall in the international price of oil constituted a brake on government spending. In addition to this situation, the phenomena of drug trafficking, violence due to the presence of the armed conflict, and fiscal corruption also had a negative impact on growth.

From a political perspective, Colombia has had one of the longest internal conflicts in the Americas. The problem started with violence between political parties, poverty, the clientelist political system, kidnapping and extortion, drug trafficking, and other factors (Pizarro, 2015). In the 1960s, left-wing rebel groups like the Revolutionary Armed Forces of Colombia-People's Army (FARC-EP) formed in remote areas. Right-wing paramilitary groups then tried to stop the rebels. This conflict has negatively affected millions of Colombians over many years (Comisión de la Verdad, 2022).

Some important events include peace deals in the 1990s with the April 19 Movement (M-19) and the Popular Liberation Army (EPL), failed talks between the government and the Revolutionary Armed Forces of Colombia-People's Army (FARC-EP) in the early 2000s, the Plan Colombia program, and a peace process that ended in a 2016 agreement (Ríos-Sierra, 2023). Victims have experienced forced displacement, land loss, kidnappings, murders, and other crimes (Pizarro, 2015).

Regarding corruption, this phenomenon has been persistent throughout the entire period, and far from decreasing, reports of it have become more frequent and significant. Thus, the constant illegal diversion of public resources affects trust in the country's institutions and, therefore, has an impact on economic growth.

ISSN: 1695-7253 e-ISSN: 2340-2717

Table 1.
Departmental descriptive statistics

Statistic	GDP per labour force (U$ 2015)		Avg. Annual Growth (%)
	1991	2017	
Average	17,187	11,558	-0.06
Minimum	4,535	5,065	-3.32
Maximum	66,410	25,340	4.98
10% quantile	6,332	6,894	-2.70
90% quantile	51,175	18,955	2.83
Standard deviation	15,950	5,403	
Variation coefficient	0.93	0,47	

Note: The observations correspond to the 33 departments of Colombia in 1991 and 2017.

Researchers have long debated how corruption affects economic growth, giving rise to two opposing perspectives. The first view is that corruption can actually help economic growth, 'grease the wheels' idea. The argument is that different types of payments to government officials can act as a lubricant, helping economic development and making bureaucratic processes faster. Supporters of this view include Acemoglu and Verdier (1998), who said corruption can make the economy more efficient and help growth. The second view is called the 'sand the wheels' idea. This view says that corruption causes problems by reducing efficiency and creating barriers to economic growth. Corruption, it argues, lowers GDP per capita growth, makes business transactions and trade harder, reduces investment, between others problems. Researchers like Mauro (1995), Tanzi and Davoodi (1998), and Rose-Ackerman and Palifka (2016) support this view.

The regional-level view of these ideas suggests that under the first perspective, an increase in corruption in nearby regions would actually help growth in each region. This would strengthen the initially positive effect. But under the second perspective, an increase in corruption in nearby regions would instead cause lower growth in each region. This would reinforce the expected negative impacts of the second view. In other words, the regional effects work in opposite ways depending on which overall perspective on corruption is correct.

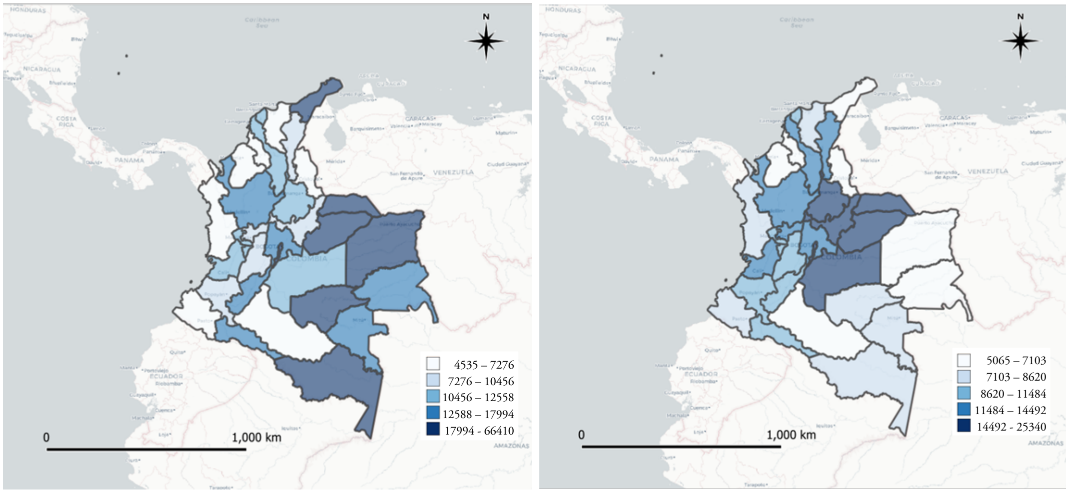
In summary, all the factors mentioned had an impact on the regional and national economy and labor productivity, some benefiting growth and productivity efficiency, and others affecting this performance and economic growth.

Figure 1 shows the departmental geographical distribution of per-employee production, GDPpl, for the years 1991 and 2017 (quintile map). In 1991, among the departments classified in the highest quintile, we found Arauca, Casanare, Vichada, and Guaviare (see Appendix B for a complete location of each department of Colombia). The first two are oil producers with the highest GDPpl, and the other two are small regions and recipients of resources assigned by the nation, but they do not stand out as important spaces for generating employment. The departments of Amazonas and La Guajira also stand out in this group, located in large territories with sparse populations. Between this quintile, the department with the highest non-oil GDP is Bogotá, which has productive strength in most sectors except for the primary sector. The two classes with less productivity (GDPpl between 10,456 and 12,558 dollars and GDPpl between 7,276 and 10,456 dollars, respectively) have similar characteristics to the departments specialized in non-oil sectors. The class with the lowest productivity (GDPpl between 4,535 and 7,276 dollars) agglomerates seven departments: Caquetá, Chocó, Córdoba, Magdalena, Nariño, Norte de Santander, and Sucre.

The distribution of GDPpl in 2017 presents different characteristics to the previous reference year, with interesting departmental conformations in the quintiles. The class with highest values (GDPpl between 14,492 and 25,340 dollars) shows a significant reduction in worker income of more than 2.5 times compared to the highest values recorded in 1991. Within this class are three of the seven departments registered in 1991, except for the island of San Andrés: the oil-producing departments Arauca, Casanare, and now Meta; Bogotá without the agricultural sector, and the departments of Santander and Boyacá, specialized in some productive sectors but not dependent on energy. Within the class of departments with GDPpl between 11,484 and 14,492 dollars, the Andean departments of Antioquia, Valle del Cauca, Caldas, and Cundinamarca have a relatively greater focus on the agricultural and manufacturing sectors, while the departments of Bolívar and Cesar, located on the Atlantic coast, have a similar orientation.

Figure 1.
Geographic distribution of GDP per labor force (1991 and 2017)

GDPpl by department (1991) GDPpl by department (2017)

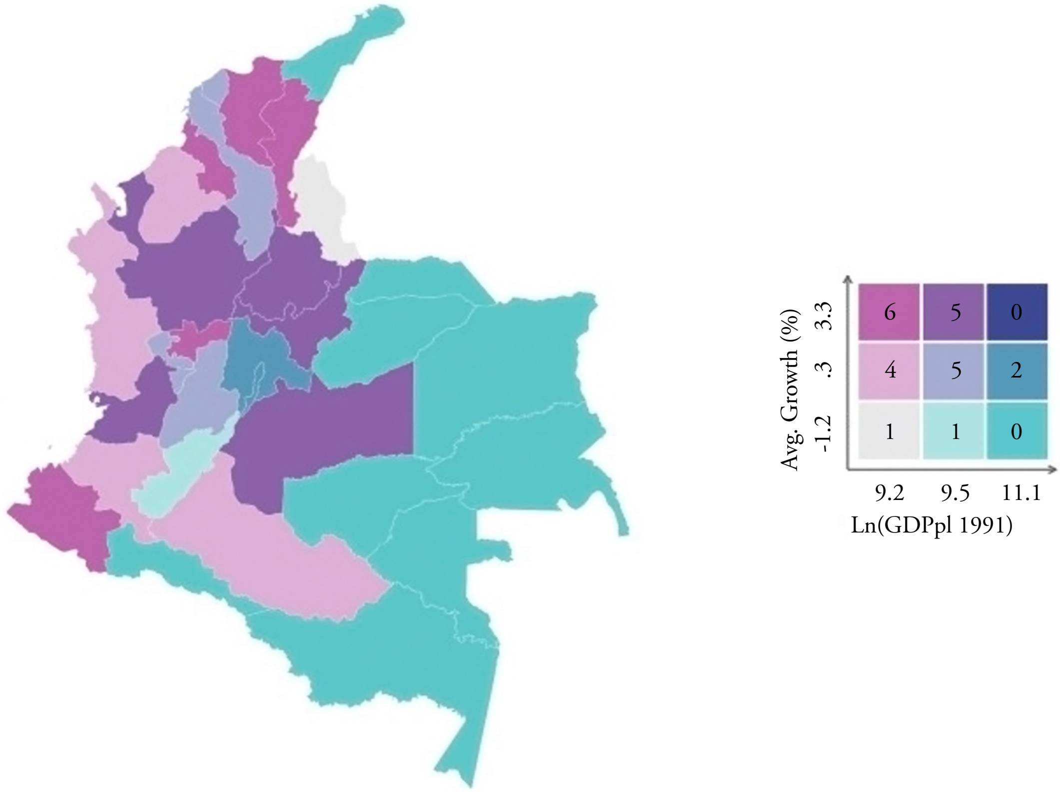


Note: Own elaboration based on National Administrative Department of Statistics (DANE) and additional sources (see Appendix A).

Figure 2 shows a bivariate map that reflects the composition of the departments around the negative relationship between economic growth from 1991-2017 and the logarithm of the 1991 GDPpl. In the first quadrant, a group of six departments with a relatively low logarithm of GDPpl in 1991 are located, with high values in the variable plotted on the y-axis (average growth of GDPpl, 1991-2017), surrounded by departments with low values in the variable plotted on the x-axis (logarithm of GDPpl in 1991); these departments are Cesar, Magdalena, Nariño, San Andrés, Sucre, and Caldas. In the quadrant located in the extreme lower right, nine departments are grouped with low values in the variable plotted on the y-axis (average growth of GDPpl, 1991-2017), surrounded by high values of the logarithm of GDPpl in 1991; these departments correspond to the regions such as La Guajira and the new departments, two of them being oil-producing.

The Figure 2 conveys a crucial message that the color scheme employed effectively clarifies the correlation between variables. Notably, the main diagonal of the box contains 20 out of the 33 departments, indicating a prevalent negative association between growth and initial GDPpl.

FIGURE 2.
Bivariate map between Avg. Growth 1991-2017 and the logarithm of GDPpl in 1991



Note: Own elaboration based on National Administrative Department of Statistics (DANE) and additional sources (see Appendix A).

4. Empirical Results

Table 2 presents five alternative specifications of the beta-convergence model considering fixed effects (FE). These models are a-spatial, in the sense that they do not incorporate any spatial lag in their specification. In the case of Model 1, no violence and corruption variable is included, representing the traditional convergence model. Models 2, 3, and 4 individually incorporate violence and corruption variables, and Model 5 includes both mentioned variables together.

All models in Table 2 find statistically significant evidence of beta-convergence, with a stable coefficient ranging between -0.034 and -0.038, throughout the different specifications. Regarding the rest of the variables, a negative and significant effect of corruption rate on growth is observed in both the simple model (Model 3) and the extended model (Model 5). In the case of violence variables, neither the victim rate nor the damage rate exerts a significant influence on growth in any of the specifications.

Additionally, Table 2 presents the Moran's I test (Moran, 1950) and the CD test by Pesaran (2004, 2021). Both tests hypothesize non-spatial autocorrelation. In the case of Moran's I, the null hypothesis includes the specification of the W matrix (defined as an exponential function of distance). In the case of the CD test, an average correlation between pairs of cross-sectional units is estimated using the temporal dimension, without the need to define a W (Pesaran, 2004). Both tests reject the null hypothesis, indicating the need to incorporate spatial effects and indicating a spatial specification error.

TABLE 2.
Estimations of non-spatial fixed effects models

Var. Dep.: $\Delta\ln(y_t)$	Model 1		Model 2		Model 3		Model 3		Model 5	
$\ln y_{t-1}$ $(\hat{\beta}_1)$	-0.036	**	-0.034	**	-0.038	***	-0.036	**	-0.037	**
	(0.016)		(0.016)		(0.016)		(0.016)		(0.016)	
$\left(\frac{Victims}{Pop.}\right)_{t-1}$ $(\hat{\beta}_2)$			0.002						0.001	
			(0.002)						(0.002)	
$\left(\frac{Corrup}{GDP}\right)_{t-1}$ $(\hat{\beta}_3)$					-2.035	**			-1.864	**
					(0.762)				(0.884)	
$\left(\frac{Damage}{GDP}\right)_{t-1}$ $(\hat{\beta}_4)$							-0.000		-0.005	
							(0.068)		(0.067)	
Controls	Yes		Yes		Yes		Yes		Yes	
Moran I (W)	0.072	***	0.071	***	0.071	***	0.072	***	0.070	***
Pesaran CD	13.621	***	13.559	***	13.637	***	13.621	***	13.607	***

Note: *** p<0.01, ** p<0.05, * p<0.1; 891 observations (n=33, T=27). Robust standard errors in parentheses. Constant omitted. Controls: $\ln(K/GDP)_t$ and $\ln gn_t$, and dummies for extreme values. W: $\exp(-2d_{ij})$, where d_{ij} is the distance between neighbors.

Table 3 presents alternative models that seek to improve the previous specification by including spatial effects under the most common specifications. The results highlight that the more complex models (SARAR, SDM, and SDEM) are not suitable and over-specify the model. In the case of SARAR, the inclusion of an endogenous spatial lag and another in the error term generates non-significance of both terms, reducing this model to a non-spatial model like the one presented in Table 2, Model 5, without solving the omission of spatial autocorrelation.

TABLE 3.
Estimations of spatial fixed effects models

Var. Dep.: $\Delta\ln(y_t)$	SAR		SEM		SDM		SDEM		SARAR	
$\ln(y_{t-1})$ $(\hat{\beta}_1)$	-0.038	**	-0.045	**	-0.043	***	-0.046	**	-0.043	**
	(0.015)		(0.018)		(0.018)		(0.019)		(0.019)	
$\left(\frac{Victims}{Pop.}\right)_{t-1}$ $(\hat{\beta}_2)$	0.001		0.001		0.000		0.001		0.001	
	(0.002)		(0.002)		(0.003)		(0.003)		(0.002)	
$\left(\frac{Corrup}{GDP}\right)_{t-1}$ $(\hat{\beta}_3)$	-1.807	**	-1.768	**	-1.776	*	-1.088		-1.795	**
	(0.920)		(0.906)		(1.044)		(1.150)		(0.885)	
$\left(\frac{Damage}{GDP}\right)_{t-1}$ $(\hat{\beta}_4)$	-0.012		-0.038		-0.026		0.010		-0.034	
	(0.068)		(0.081)		(0.074)		(0.076)		(0.074)	
$W\ln(y_{t-1})$ $(\hat{\theta}_1)$					0.076		0.125			
					(0.053)		(0.077)			
$W\left(\frac{Victims}{Pop.}\right)_{t-1}$ $(\hat{\theta}_2)$					0.007		0.015	*		
					(0.004)		(0.008)			
$W\left(\frac{Corrup}{GDP}\right)_{t-1}$ $(\hat{\theta}_3)$					3.428		6.430			
					(6.891)		(11.374)			

TABLE 3. CONT.
Estimations of spatial fixed effects models

Var. Dep.: $\Delta\ln(y_t)$	SAR		SEM		SDM		SDEM		SARAR	
$W\left(\frac{Damage}{GDP}\right)_{t-1}$ $(\hat{\theta}_4)$					0.825		1.642			
					(1.150)		(1.542)			
$W\Delta\ln(y_t)$ $(\hat{\rho})$	0.476	***			0.470	***			0.209	
	(0.100)				(0.102)				(0.403)	
Wu $(\hat{\lambda})$			0.545	***			0.537	***	0.402	
			(0.092)				(0.089)		(0.304)	
Test Wald (H_0:SAR)					5.55					
Test Wald (H_0:SEM)							6.33			
Test C. F. (H_0:SEM)					4.36					
AIC	-1914.86		-1902.62		-1911.01		-1900.15		-1901.05	
BIC	-1876.83		-1831.30		-1853.95		-1809.81		-1824.97	

Note: *** p<0.01, ** p<0.05, * p<0.1; 891 observations (n=33, T=27). Robust standard errors in parentheses. Constant omitted. Controls: $\ln(K/GDP)_t$ and $\ln gn_t$, and dummies for extreme values. W: $\exp(-2d_{ij})$, where d_{ij} is the distance between neighbors.

Disregarding the SARAR model, Durbin models are the most complex in their specification. By using Wald tests, evidence can be obtained to discard these Durbin models, SDM and SDEM, in favor of simpler spatial models such as SAR and SEM. The C.F. test is known as "common factors" and is a version of Wald that tests the null hypothesis of the nonlinear restriction $(\theta = -\rho\beta)$ such that under this restriction, the SDM model can be written as an SEM. The information provided by the three tests suggests the incorporation of spatial dependence through an SEM or SAR model.

Between the two most competent models, SAR and SEM, the model that best fits the data in terms of AIC and BIC criteria is the SAR. One noteworthy point in SAR and SEM spatial models, and even those more complex models that were discarded, is the significant detection of beta-convergence and the negative impact of corruption on economic growth.

The SAR model is a type of static model in terms of temporal dependence (the time lag of the dependent variable is not introduced as an explanatory variable) and requires further inspection to determine if its specification is the most appropriate. By checking for serial correlation in the residuals of the SAR, it is possible to determine whether temporal dynamic elements have been omitted or not. Following Millo (2015), a version of the Wooldridge (2010) test was applied for an AR(1) and a value of $F = 12.13$ was obtained, rejecting the null hypothesis of no serial correlation for the SAR model at 1%. Consequently, the SAR model should be expanded to include space-time dependence, and we follow the models proposed by Yu and Lee (2012) and Anselin et al. (2008) for this purpose.

Table 4 presents a summary of the main dynamic spatial models: SDPD model, recursive model, and simultaneous model. Additionally, a non-spatial dynamic model is included using the standard approach proposed by Arellano and Bond (1991).

The most complex model, the SDPD model, meets the stationarity requirements, $(\rho + \tau + \eta < 1)$, although it fails to meet the parametric restriction for identification between space-time effects $(\eta = -\rho\tau)$. Among the simultaneous and recursive models, the latter model fits the data best according to

AIC/BIC and also contains a significant spatial recursive parameter, making it the best model among all the explored alternatives.

The dynamic models, Simultaneous and SDPD, which incorporate an autoregressive lag, $\Delta\ln(y_{t-1})$, do not detect significance in this coefficient. In the case of the models that incorporate the variable $W\Delta\ln(y_{t-1})$, the Recursive and SDPD models, detect a significant coefficient of this variable. It can also be observed that the coefficient of the temporal lag present in the SDPD, Simultaneous, and Non-spatial models is not significant, evidencing weak temporal persistence within each region of economic growth. The same does not happen with the coefficients of the spatial lags, where it is observed that the contemporary spatial effect, $W\Delta\ln(y_t)$, is significant in all models. In addition, the spatial-temporal lag, $W\Delta\ln(y_{t-1})$, reflects that there is a temporal transmission of the behavior in economic growth of geographic neighbors, given us the main reason for controlling for the spatial-temporal persistence of economic growth. The coefficient of the spatial-temporal lag can be interpreted as a measure of the relative transmission of time in which a particular region is affected by the behavior of its neighbors.

As previously happened in static models, in all models in Table 4, a significantly negative coefficient of the variable $\ln(y_{t-1})$ is detected, confirming the hypothesis of beta-convergence. Additionally, as in previous specifications, corruption shows a significant effect in each of the spatial-temporal dynamic models.

TABLE 4.
Estimations of dynamic spatial fixed effects models.

Var. Dep.: $\Delta\ln(y_t)$	Non-spatial Model		Simultaneous Model		Recursive Model		SDPD Model	
$\ln(y_{t-1})$ $(\hat{\beta}_1)$	-0.037	*	-0.042	**	-0.042	***	-0.045	***
	(0.021)		(0.017)		(0.016)		(0.016)	
$\left(\frac{Víctimas}{Pob.Tot.}\right)_{t-1}$ $(\hat{\beta}_2)$	0.003		0.000		-0.000		-0.000	
	(0.002)		(0.002)		(0.002)		(0.002)	
$\left(\frac{Corrup}{PIB}\right)_{t-1}$ $(\hat{\beta}_3)$	-0.385		-1.457	**	-1.443	**	-1.527	**
	(0.827)		(0.707)		(0.730)		(0.711)	
$\left(\frac{Daño}{PIB}\right)_{t-1}$ $(\hat{\beta}_4)$	-0.095		-0.028		-0.020		0.027	
	(0.080)		(0.062)		(0.068)		(0.061)	
$\Delta\ln(y_{t-1})$ $(\hat{\tau})$	0.076		0.081				0.063	
	(0.077)		(0.076)				(0.085)	
$W\Delta\ln(y_{t-1})$ $(\hat{\eta})$					0.327	***	0.287	*
					(0.114)		(0.151)	
$W\Delta\ln(y_t)$ $(\hat{\rho})$			0.475	***	0.455	***	0.448	***
			(0.103)		(0.106)		(0.109)	
Wald test: (H0: $\eta = -\rho\tau$)							6.57	***
Stationarity: $(\tau + \rho + \eta)$<1			Yes		Yes		Yes	
AIC			-1943.97		-1951.15		-1950.25	
BIC			-1901.17		-1908.36		-1902.70	

Note: *** p<0.01, ** p<0.05, * p<0.1; 891 observations (n=33, T=27). Robust standard errors in parentheses. Constant omitted. Controls: $\ln(K/GDP)_t$ and $\ln gn_t$, and dummies for extreme values. W: $\exp(-2d_{ij})$, where d_{ij} is the distance between neighbors.

In terms of model fitting capability, the Recursive model is the one that best captures the growth dynamics and is the preferred model among alternative specifications. Once the most suitable specification is chosen, we need to delve into interpreting the results. A peculiarity of spatial models, whether static or dynamic, is that the interpretation of coefficients cannot be directly done as in the usual case of models obtained by Ordinary Least Squares. The problem lies in the presence of endogenous spatial lag for the SAR case, $W\Delta\ln(y_t)$, and spatial lags $W\Delta\ln(y_t)$ and $W\Delta\ln(y_{t-1})$ in the Recursive model. These elements generate a feedback among the units of analysis such that we do not have a single marginal effect but a matrix of effects that are difficult to read and modify the direct reading of beta coefficients. For instance, in the case of the SAR model, each β_k coefficient is pre-multiplied by $(I_n - \rho W)^{-1}$, under $|\rho| < 1$, such that the coefficient is pre-multiplied by a term greater than unity:

$$\left[\frac{\partial E\Delta\ln(y)}{\partial x_{1k}} \dots \frac{\partial E\Delta\ln(y)}{\partial x_{nk}}\right] = (I_n - \rho W)^{-1}\beta_k I_n, \ \ \forall t$$

The literature has proposed summary measures of these effects, both direct and indirect, by estimating average effects. For the static SAR model, these effects are calculated as follows:

- Average Direct effect of x_k:

$$[(I - \rho W)^{-1} \times \beta_k I_n]^{\bar{d}}$$

- Average Indirect effect of x_k:

$$[(I - \rho W)^{-1} \times \beta_k I_n]^{\overline{rsum}}$$

being the superscript $\bar{d}$ the operator that calculates the average of the elements on the main diagonal of the matrix, and the superscript $\overline{rsum}$ representing the operator that calculates the average of the sums of the non-diagonal elements in each row of the matrix. These effects are considered long-term for the static SAR model.

In the case of dynamic models, they have the advantage of allowing for direct and indirect average effects, both short-term and long-term. For example, under the Recursive model, long-term effects are obtained by assuming that a steady state is reached such that the difference between growth in period t and 1 is zero ($\Delta ln(y_t) \ = \ \Delta ln(y_{t-1}) \ = \ \Delta ln(y^*)$). In this way, the matrix of partial derivatives for the expected value of with respect to a change in a unit of the $k-th$ explanatory variable in the n regions can be obtained as follows:

$$\left[\frac{\partial E\Delta\ln(y^*)}{\partial x_{1k}} \dots \frac{\partial E\Delta\ln(y^*)}{\partial x_{nk}}\right] \ = [(I_n - (\rho + \eta)W]^{-1}\beta_k$$

This expression can be decomposed into a direct average effect and an indirect one, similar to what was seen for the SAR model. In particular, for the Recursive model, long-term effects are obtained through:

- Average Direct effect of x_k:

$$[(I - (\rho + \eta)W)^{-1} \times \beta_k I_n]^{\bar{d}}$$

- Average Indirect effect of x_k:

$$[(I - (\rho + \eta)W)^{-1} \times \beta_k I_n]^{\overline{rsum}}$$

In addition, short-term effects are represented by:

- Average Direct effect of x_k:

$$[(I - \rho W)^{-1} \times \beta_k I_n]^{\bar{d}}$$

- Average Indirect effect of x_k:

$$[(I - \rho W)^{-1} \times \beta_k I_n]^{\overline{rsum}}$$

Table 5 summarizes the average direct and indirect effects for the best-fitting SAR and Recursive models, considering the short-run and long-run decomposition. In addition, we conducted a robustness check using an alternative W, using an inverse squared-distance function, and found similar results (these results are presented in Appendix C).

The estimated average indirect effects of the explanatory variables should be used to test the hypothesis of spatial spillovers, instead of relying on the estimation of the coefficient of $W\Delta ln(y_t)$ and/or the coefficient estimates of $W\Delta ln(y_{t-1})$. However, the difficulty lies in obtaining the standard errors of these effects, and consequently, the corresponding t-tests values. This is because the indirect effects are composed of different coefficient estimates according to complex mathematical formulas, and the dispersion of these indirect effects depends on the dispersion of all involved coefficient estimates. For instance, as highlighted by (Elhorst, 2014, p. 24), if the SAR model coefficients ρ and β_k are significant, it does not necessarily mean that the indirect effect of the $k-th$ explanatory variable is also significant. Conversely, even if one or two of these coefficients are non-significant, the indirect effect can still be significant.

One possible way to calculate the dispersion of direct and indirect effects and thus obtain inferences regarding their statistical significance is through Monte Carlo simulation, where random shocks are applied to the implicit variance-covariance matrix of maximum-likelihood estimates to approximate the distribution of direct and indirect effects (LeSage and Pace, 2009, p. 39). Alternatively, the well-known Delta method based on the asymptotic Normal distribution can be used to obtain the standard error of the average direct and indirect effects, which was applied in this study.

Table 5 presents the long-run effects obtained by the SAR model, showing significant average impacts of the two most relevant variables, $\ln(y_{t-1})$ and $\left(\frac{Corrup}{GDP}\right)_{t-1}$. In the case of the corruption variable, a significant impact can be observed for the direct, indirect, and total effects, significant at least at the 10% level. This result holds for the Recursive model, although in this case, only a significant impact of the short- and long- run direct effect is detected. No significant spillover effect of corruption is detected in the short or long run. The results from the recursive spatial model provide evidence that corruption has localized impacts on economic growth, mostly affecting each region directly rather than spilling over significantly into neighboring areas. Furthermore, the impact is mainly short-term, without finding evidence of a corruption effect on long-term growth. Our findings support the view that corruption 'sands the wheels' of development, rather than the 'grease the wheels' perspective that corruption can help compensate for poor governance. This aligns with the conclusions drawn by de Paulo et al. (2022), who reached similar results for Latin American and Caribbean countries using an alternative corruption measure. At the regional level, Truong (2020) also found comparable results regarding the impact of corruption in different regions of Vietnam. This cross-regional evidence further reinforces the detrimental effect of corruption on development, regardless of the specific geographic context.

Another important result concerns the coefficient of the variable $\ln(y_{t-1})$. Both models provide evidence of beta convergence in the sense that this coefficient is negative, but there is a clear discrepancy in the decomposition between the short and long term. Under the SAR model, the long-term direct and indirect effects show a significant impact that reinforces each other, resulting in a convergence rate of 0.073. However, under the Recursive model, which allows for a decomposition of effects between the short and long term, convergence is achieved in both the direct and indirect effects in the short term, and the total effect rate of 0.077 is very close to that presented by the SAR model. However, this strengthening behavior of convergence via direct and indirect effects is not accompanied in the long term, and only the direct effect is significant at a rate of 0.046. That is, there is no evidence that neighboring regions help economic convergence in the long term, and this convergence is of a more internal nature to each department. Finally, the effects of damages and victims are not significant in any of the average effects.

 ISSN: 1695-7253 e-ISSN: 2340-2717

TABLE 5.
Marginal effects of static and dynamic model

	SAR Model						Recursive Model					
	Short-run effects											
	Directs		**Indirects**		**Totals**		**Directs**		**Indirects**		**Totals**	
$\ln(y_{t-1})$							-0.042	***	-0.034	*	-0.077	**
							(0.016)		(0.019)		(0.032)	
$\left(\frac{Victims}{Pop.}\right)_{t-1}$							-0.000		-0.000		-0.000	
							(0.002)		(0.002)		(0.004)	
$\left(\frac{Corrup}{GDP}\right)_{t-1}$							-1.462	**	-1.186		-2.647	*
							(0.740)		(0.803)		(1.461)	
$\left(\frac{Damage}{GDP}\right)_{t-1}$							-0.020		-0.016		-0.036	
							(0.069)		(0.059)		(0.128)	
	Long-run effects											
	Directs		**Indirects**		**Totals**		**Directs**		**Indirects**		**Totals**	
$\ln(y_{t-1})$	-0.039	**	-0.034	*	-0.073	**	-0.046	**	-0.146		-0.192	
	(0.015)		(0.019)		(0.031)		(0.018)		(0.132)		(0.145)	
$\left(\frac{Victims}{Pop.}\right)_{t-1}$	0.001		0.001		0.001		-0.000		-0.001		-0.001	
	(0.002)		(0.002)		(0.004)		(0.002)		(0.007)		(0.009)	
$\left(\frac{Corrup}{GDP}\right)_{t-1}$	-1.834	**	-1.615	*	-3.448	*	-1.572	*	-5.048		-6.621	
	(0.932)		(0.981)		(1.799)		(0.848)		(5.322)		(6.051)	
$\left(\frac{Damage}{GDP}\right)_{t-1}$	-0.012		-0.011		-0.023		-0.021		-0.068		-0.090	
	(0.069)		(0.063)		(0.133)		(0.075)		(0.273)		(0.348)	

Note: Own elaboration

5. Conclusions

This paper focused on the regional economic growth for Colombia throughout the period of 1991-2017. As in most developing countries, Colombia shows a history of social problems related to violence and corruption, all of which are linked to heterogeneous growth among regions.

Starting from a beta convergence model, we use recent spatial extensions for panel data taking GDP per labor force as the dependent variable, robust evidence of beta convergence is found in both a-spatial and spatial static and dynamic specifications. This implies that regions with a low initial level of income per worker tend to grow faster than regions with a high initial level of income per worker, conditioned by the other explanatory variables in alternative models. The results obtained and presented are relevant for clarifying the evidence presented throughout the Colombian literature. A recent study on regional convergence by Acosta and Bonet-Morón (2022), which incorporates regional spatial dependence during the period of 2000-2020, presents results similar to those obtained in this research.

Regarding the impact of factors conditioning, armed violence and fiscal corruption, there is evidence of a significant impact of the latter factor in each presented model. Under the Recursive model, which is the model that best fits the data, the incidence of corruption is mainly short-term, without showing significant spillover effects in the long term. The results obtained highlight the need to incorporate spatio-temporal models in the discussion of economic growth to detect short- and long-term spatiotemporal dynamics.

On the side of armed conflict, as part of the pacification of the country, the peace agreement signed in 2016 between the state and the guerrilla group FARC-EP was promoted, which is advancing with many administrative limitations. On the other hand, the incorporation of policies and measures for the prevention and control of fiscal corruption, according to internal needs and recommendations from international organizations, among other anti-corruption measures, include: criminal, disciplinary sanction, and fiscal responsibility codes; however, this problem for the country and its departments is complex, so much so that this phenomenon is consolidated and persists over time.

In future developments, there is a plan to extend the observation period to include recent significant events like the peace agreement, the pandemic, and the war in Ukraine. Additionally, there is a need to expand the explanatory covariates within the models. It is particularly valuable to examine how alternative measures of corruption and violence affect the variable of interest.

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Appendixes

Appendix A: Source of Information

The source of information of main variables used is the follows:

1. Gross Domestic Product (GDP) for each department for the period 1990 to 2017, were obtained from the National Administrative Department of Statistics (DANE, 2019): https://www.dane.gov.co/index.php/estadisticas-por-tema/cuentas-nacionales/agregados-macroeconomicos-retropolacion-base-2015
2. Departmental Population was obtained as follows:
    a) Primary source: Censuses 1985, 1993, 2005 and 2018 for each department;
    b) The data for the years 1990 to 1992, 1994 to 2004 and 2006 to 2017, was constructed by this research through projections by the geometric method.
3. Working population (labor force) corresponds to people who have a paid job or exercise an independent activity and have worked at least one hour during the reference week and those who, not having done so, maintain a formal link with their employment (International Labor Organization, ILO). The final information was collected and constructed as follows:
    c) Years 1990 to 1992, information constructed for all departments, through estimates made by the univariate method of time series with GRETL software.
    d) Year 1993, corresponds to information from the census conducted by DANE;
    e) Years 1994 and 1995, are projections made by this research based on the 1993 census. The data for each department are available on the DANE website;
    f) Period 1994 to 2017, are figures provided by DANE for 24 territories, except for the new departments (9), whose data were obtained through projections using the mathematical method that contemplates continuous growth.
    g) The initial basis for the figures was obtained from the DANE website: https://www.dane.gov.co/index.php/estadisticas-por-tema/mercado-laboral
4. The Gross Fixed Capital Formation (GFCF) comes from the records of the Effective Cash Operations (OEC), both at the departmental and municipal levels. The data were taken at the departmental level and expressed in constant 2015 pesos. The source information is available on the website of the National Planning Department (DNP): https://www.dnp.gov.co/programas/desarrollo-territorial/Estudios-

Territoriales/Informacion-Presupuestal/Ejecuciones-Presupuestales/Paginas/Operaciones%20Efectivas%20de%20Caja.aspx.

5. The variable Victims considers all persons who, individually or collectively, have suffered harm due to the effects of the internal armed conflict, which occurred in each of Colombia's departments during the period 1990 to 2017. The data were obtained from the website of the Unit for Attention and Integral Reparation to Victims, available in the chapter of the Single Registry of Victims (RUV): https://www.unidadvictimas.gov.co/es/registro-unico-de-victimas-ruv/37394

6. The Damages due to Effects of Violence corresponds to quantified damages due to actions of the internal armed conflict. The information for this variable was aggregated for this research based on the records of the following actions: extortion, rustling and terrorism. Extortion is a crime consisting of forcing a person, through the use of violence and threats, to perform, tolerate or omit an act against his will, with the intention of generating illicit profit or economic benefit for himself or for a third party. Rustling is the appropriation for oneself or for another of bovine, equine, porcine, ovine and caprine species. Terrorism is a situation of anxiety or terror against the population, through acts that endanger the life, physical integrity or freedom of persons or buildings or means of communication, transportation, processing or conduction of fluids or motive forces (Ministry of Justice, 2020 www.minjusticia.gov.co). The information is published in the *Revista Criminalidad de la Policía Nacional de Colombia*, Website. Records are compiled for the 32 departments and Bogotá, period 1990 to 2017. The primary data are recorded at current pesos converted by this research to 2015 constants (https://www.policia.gov.co/revista-criminalidad-todas/)

7. The variable Corruption was generated from the data and records of the Judgments with Fiscal Responsibility (*Fallos de Responsabilidad Fiscal*) that refer to an administrative act issued by the "*Contraloría General de la República*" against an entity or natural person for the improper and inadequate use of public resources that is valued as a detriment to the State's patrimony. The information was obtained from the "*Procuraduría General de la Nación*", an entity that, due to its preventive, intervention and disciplinary nature, records the information of those rulings that affect the State's assets in administrative acts called "*Fallos con Responsabilidad Disciplinaria*". The information was obtained through direct requests to the referred entities. The data provided by these entities were disaggregated at the municipal, departmental and national levels. These, according to the needs of the research, were aggregated at the departmental. These acts are measured in current values in local currency. Subsequently, they were converted from current to constant 2015 pesos.

Appendix B: Geographical Distribution of Departments of Colombia

Figure A.1.
Administrative Departments of Colombia

Appendix C: Robustness check of alternative W

Table C.1.
Estimations of dynamic spatial fixed effects models

Var. Dep.: $\Delta\ln(y_t)$	Non-spatial Model		Simultaneous Model		Recursive Model		SDPD Model	
$\ln(y_{t-1})$ $(\hat{\beta}_1)$	-0.038	*	-0.042	**	-0.042	***	-0.045	***
	(0.021)		(0.017)		(0.016)		(0.017)	
$\left(\frac{Víctimas}{Pob.Tot.}\right)_{t-1}$ $(\hat{\beta}_2)$	0.003		0.000		0.000		-0.000	
	(0.002)		(0.002)		(0.002)		(0.002)	
$\left(\frac{Corrup}{PIB}\right)_{t-1}$ $(\hat{\beta}_3)$	-0.385		-1.545	**	-1.557	**	-1.637	**
	(0.827)		(0.696)		(0.696)		(0.677)	
$\left(\frac{Daño}{PIB}\right)_{t-1}$ $(\hat{\beta}_4)$	-0.095		-0.042		-0.038		-0.045	
	(0.080)		(0.062)		(0.068)		(0.062)	

TABLE C.1. CONT.
Estimations of dynamic spatial fixed effects models

Var. Dep.: $\Delta\ln(y_t)$	Non-spatial Model		Simultaneous Model		Recursive Model		SDPD Model	
$\Delta\ln(y_{t-1})$ $(\hat{\tau})$	0.076		0.083				0.065	
	(0.077)		(0.076)				(0.084)	
$W\Delta\ln(y_{t-1})$ $(\hat{\eta})$					0.239	***	0.205	*
					(0.076)		(0.107)	
$W\Delta\ln(y_t)$ $(\hat{\rho})$			0.364	***	0.361	***	0.354	***
			(0.083)		(0.081)		(0.083)	
Wald test: (H_0: $\eta = -\rho\tau$)							7.38	***
Stationarity: $(\tau + \rho + \eta)<1$			Yes		Yes		Yes	
AIC			-1944.22		-1950.78		-1950.05	
BIC			-1901.43		-1907.98		-1902.50	

Note: *** p<0.01, ** p<0.05, * p<0.1; 891 observations (n=33, T=27). Robust standard errors in parentheses. Constant omitted. Controls: $\ln(K/GDP)_t$ and $\ln gn_t$, and dummies for extreme values. W: $(d_{ij})^{-2}$, where d_{ij} is the distance between neighbors.

TABLE C.2.
Marginal effects under alternative W

	SAR Model						Recursive Model					
	Short-run effects											
	Directs		Indirects		Totals		Directs		Indirects		Totals	
$\ln(y_{t-1})$							-0.043	***	-0.023	*	-0.065	**
							(0.016)		(0.012)		(0.026)	
$\left(\frac{Victims}{Pop.}\right)_{t-1}$							0.000		0.000		0.000	
							(0.002)		(0.001)		(0.003)	
$\left(\frac{Corrup}{GDP}\right)_{t-1}$							-1.583	**	-0.853		-2.436	**
							(0.711)		(0.521)		(1.182)	
$\left(\frac{Damage}{GDP}\right)_{t-1}$							-0.039		-0.021		-0.060	
							(0.069)		(0.041)		(0.110)	
	Long-run effects											
	Directs		Indirects		Totals		Directs		Indirects		Totals	
$\ln(y_{t-1})$	-0.039	**	-0.022	*	-0.061	**	-0.044	***	-0.060	*	-0.105	**
	(0.015)		(0.011)		(0.025)		(0.017)		(0.035)		(0.049)	
$\left(\frac{Victims}{Pop.}\right)_{t-1}$	0.001		0.000		0.001		0.000		0.000		0.000	
	(0.002)		(0.001)		(0.003)		(0.002)		(0.003)		(0.005)	
$\left(\frac{Corrup}{GDP}\right)_{t-1}$	-1.938	**	-1.073	*	-3.011	**	-1.649	**	-2.238		-3.887	*
	(0.915)		(0.613)		(1.457)		(0.754)		(1.558)		(2.250)	
$\left(\frac{Damage}{GDP}\right)_{t-1}$	-0.025		-0.014		-0.039		-0.041		-0.055		-0.096	
	(0.069)		(0.041)		(0.110)		(0.073)		(0.114)		(0.186)	

Note: Own elaboration.