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Impact factors and space-time characteristics of income inequality in a global sample

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Abstract

Inequality has been of growing interest in the political debate and in theoretical and empirical studies for some decades. Therefore, the study of regional inequality raises some relevant questions related to the spatial nature of the data. In fact, adopting a regional point of view implies the opportunity to consider spatial interactions, which traditional studies do not include in their analyses. Therefore, the study aims to analyze income inequality before (*GINI*1) and after (*GINI*2) income and transfers, using a data set of 116 countries during a time period from 1985 to 2018. Spatial Durbin and Spatial Lag Models are applied to address spatial interactions and the spillover effect between countries and regions. First, the estimation results verify the existence of spatial correlations in income inequality for both *GINI*1 and *GINI*2. Second, both *GINI*1 and *GINI*2 produce relatively similar scenarios, which implies that the effects of the independent variables do not differ in both scenarios. Third, globalization widens the income differences of neighboring regions significantly. Fourth, urbanization has a negative and significant effect, which generates a spillover effect and reduces the inequality of neighboring economies. Finally, there is evidence that an inverted Kuznets U is rejected both for economic and financial development. Thus, inequality at the regional level provides useful insights for policy makers, as it facilitates the assessment of the effectiveness of strategies aimed at reducing regional disparities and helps to develop actions based on the location and its environment.

KEYWORDS

global sample, income inequality, Kuznets inverted U, spatial panel data, spillovers

1 | INTRODUCTION

Inequality as a central topic of analysis has found a place in the literature since the existence of the economy itself. However, the relationship with economic growth has gained special relevance in recent years due to studies such as that of Piketty (2014). In addition, considerable efforts have been made in the recent literature to understand this positive or negative relationship and estimate the nonlinear relationship between inequality and growth in more developed economies (Achten & Lessmann, 2020; Blanco & Ram, 2019; Meniago & Asongu, 2018; Mieres Brevis, 2020; Sayed & Peng, 2020). This is based on the approach developed by Kuznets (1955), who suggested that the relationship between economic growth and income inequality appears to be in the form of an inverted U (income distribution changes from relative equality to inequality and returns to greater inequality as the country develops). Since Kuznets (1955), a considerable number of studies have been conducted in an attempt to estimate the inverted U-shaped relationship between inequality and growth (Amos Jr, 1988; Bahmani-Oskooee & Gelan, 2008; Fields, 1987; Jacobsen & Giles, 1998; Ram, 1991; Shahbaz, 2010). Recent studies explore this relationship in several countries by using panel, cross-sectional, and time-series data (McCalman, 2018; Osakwe et al., 2018; Saha & Mishra, 2020).

On the other hand, several empirical studies highlight the crucial role of finance and a strong and efficient financial system in enhancing economic growth and development, as they contribute to boosting total productivity and promoting market-driven dynamics (Altunbaş & Thornton, 2019; Bittencourt et al., 2019; Chiu & Lee, 2019; Kavya & Shijin, 2020; Quito, Ponce, et al., 2021). Furthermore, the literature shows evidence linking financial development to income inequality, proposing that in particular cases, there are benefits in the reduction, such as Van Velthoven et al. (2019), whereas in other cases, the effect is the opposite and exacerbates the problem of inequality (Jung & Cha, 2021). However, most of the literature has neglected spatial issues, which can influence inequality and play a relevant role in the growing interest of the political debate.

Therefore, regional interconnections and the reciprocal influence between regions must be considered when analyzing inequality at the regional level. In fact, as in the case of other economic phenomena, regional disparities are likely to be affected by the presence of neighborhood effects in the form of spatial dependence (Anselin, 1988). Some more recent literature has been proposed in this direction. For example, Achten and Lessmann (2020), Puškárová and Vašková (2021), and Ponce et al. (2021) focused on the relevance of spatial effects when discussing economic and social disparities, since the territorial dimension is considered fundamental to address inequalities.

This paper aims to fill this gap in the literature, and provide a comprehensive analysis of the relationship between economic growth and financial development on income inequality in two scenarios before (*GINI*1) and after (*GINI*2) taxes and transfers, taking a global sample of 116 countries over the period 1985–2018. The methodology used in this econometric panel data study involves the use of spatial SLM-Spatial Lag Model and SDM-Spatial Durbin Model as the main ones. The results show that income inequality is spatial in behavior, both before and after taxes. On the other hand, an inverted Kuznets U is rejected for both economic and financial development. Furthermore, the models are used to validate spatial spillovers of the variables in order to provide more rigorous benchmarks for policy makers.

The paper is structured as follows. After introducing the subject under study and the objective of this research, Section 2 reviews the literature, focusing on the link between economic development and income inequality. Data and estimation methodological strategies are presented in Section 3. Section 4 reports and discusses the empirical results of the study. Finally, Section 5 presents the conclusions of the study, the implications and limitations.

2 | LITERATURE REVIEW

2.1 | Kuznets' inverted U hypothesis: Supported or not?

Understanding the relationship between economic development and income inequality has been widely discussed in the literature. Part of the earliest studies linking economic development and income inequality is Kuznets' inverted U-shaped hypothesis. Kuznets (1955) argues that the early stages of economic growth are characterized by increased inequality, while later stages are associated with lower levels of inequality. His theoretical prediction assumes a transition from agriculture to highly productive industries. However, this shift may lead to a temporary increase in income gaps, as most gains benefit only certain segments of society, and over time the increase in inequality will stabilize and decline in later stages of development. In the most recent literature, Meniago and Asongu (2018), in a sample of 48 African countries from 1996 to 2014, using the Generalized Method of Moments (GMM), found strong evidence for an inverted U-shaped link between rising GDP per capita and inequality. Likewise, Blanco and Ram (2019) suggest that in the United States between 2006 and 2016, the turning point that would support an inverted U-shape occurred when real GDP per capita reached $45,940 in 2009 dollars.

In the same vein, alternative approaches such as Jovanovic (2018), who after analyzing 26 ex-socialist countries of the former Eastern bloc, during the post-socialist years, suggest that the Kuznets curve is present only when the control of companies´ market power is effective and taxes are high. On the other hand, Wu and Yao (2015) used time series and cointegration techniques in order to validate the Kuznets hypothesis for China during 1978–2012. They found that although the government tries to balance growth, equality and short-term state ownership, stubborn state ownership and asymmetric growth patterns jeopardize long-term equality and have thus delayed the turning point of the inverted U-shaped Kuznets curve for China. Other studies validating the Kuznets inverted U hypothesis include Lyubimov (2017), Baloch et al. (2018), Wu and Li (2017).

However, as opposed to previous studies, Mieres Brevis (2020) suggests that the relationship between GDP per capita and the Gini index for Chile does not have the traditional inverted Kuznets U shape, but rather the inverse behavior. This author argues that the initial values of income, the economic activity of the region, the concentration of the indigenous population and human capital are important and robust determinants of income inequality in Chile. When considering a broader temporality, as in the study by Sayed and Peng (2020) for four developed countries (United States, United Kingdom, France, and Germany) over the period 1915–2014, they found an N-shaped curve and that the Kuznets curve does not explain this path, in which the curvature of the relationship is statistically significant. Thus, as GDP per capita increases, income inequality first increases, peaks at a level of US$4600 (on average), then decreases, reaching a minimum at a level of US$22,355 (on average), and then increases again.

On the other hand, a cluster analysis applied by Brida et al. (2020) in 38 countries from 1980 to 2015, suggests that there are mainly two groups: advanced economies (growing or stagnant with low income inequality) and poor or developing countries (growing or not, but with high levels of income inequality). In other words, as the share of capital in the growth process increases and capital substitutes labor, the growth force that reduces inequality decreases (McCalman, 2018; Osakwe et al., 2018; Saha & Mishra, 2020). Taking a closer look at spatial analyses of inequality, Achten and Lessmann (2020) conclude that national economic activity within countries harms spatial inequality and that the most unequal regions tend to form global clusters. In addition, economic activity alone does not determine the level of regional inequality, other factors, such as the structure of export products, would be linked to inequality levels (Zhu et al., 2020).

2.2 | Financial development and income inequality

The second factor affecting inequality levels involves financial development, so that it may or may not validate a financial Kuznets curve (Baiardi & Morana, 2018). In this line, the works of Chiu and Lee (2019) and Altunbaş and Thornton (2019) are presented, where the hypothesis is not fulfilled at the level of the entire sample, showing that the impact of financial development on income inequality seems to change with the income level of a country. On the other hand, in BRICS (Brazil, Russia, India, China, and South Africa), there is a nonlinear relationship that validates the Kuznets inverted U hypothesis (Younsi & Bechtini, 2020). Meanwhile, in the United States, Bittencourt et al. (2019) state that the effect of financial development seems to differ according to the level of inequality in each state, with the effect increasing in states with above-average inequality, while an inverted U-shaped relationship is observed in states with below-average inequality. Some studies show favorable results that validate a financial Kuznets hypothesis (Gharleghi & Jahanshahi, 2020; Thornton & Tommaso, 2020; Van Velthoven et al., 2019).

In contrast, Kavya and Shijin (2020) suggest for a sample of 85 countries that there is no clear evidence to support that economic development together with financial growth would reduce the problem of income inequality. Regarding the structure of financial development, both financial institutions and markets are important transmission channels for reducing income inequality in upper-middle income countries (Altunbaş & Thornton, 2020). Finally, Jung and Cha (2021) show that for China, financial development has two directions, the first one is related to an increase in economic growth and the second one exacerbating the problem of income inequality, so there is no turning point that validates a financial Kuznets curve. This is supported by a provincial-level study in China, where although there is a positive effect of economic growth, there is also a negative effect of financial development on income inequality (Lee et al., 2019).

2.3 | Globalization and income inequality

In terms of globalization and income inequality, the work of Law et al. (2020) shows that globalization widens redistribution channels, leading to a positive effect on redistribution, as does financial development. Engler and Weisstanner (2020) also suggest that there are certain economies that suffer neglect, called "globalization losers," which coincidentally have high income inequality. On the other hand, in Asia, both globalization and trade have favorable effects on reducing income inequality. However, the effect is more significant when it comes from technological globalization (Munir & Bukhari, 2020). In this same line of analysis, the results differ between economies, such is the example of the results of Mallick et al. (2020), where after confirming cointegration between the variables, the long-term results based on the ARDL model surprisingly reveal that economic globalization widens income inequality in India, but the same factor reduces income inequality in China.

3 | METHODOLOGY

3.1 | Theoretical framework of the model

The scope of this study is to identify the impact of economic development (GDP) on income inequality before and after taxes and transfers (*GINI1 and GINI2*) in a sample of 116 countries for the period 1985–2018, under the theoretical model of Kuznets (1955), that proposed the pioneering study predicting that economic development and income inequality have an inverted U-shaped relationship:

$$I_{it} = f\left(y_{it}, y_{it}^2\right) \tag{1}$$

where I_{it} represents income inequality and y_{it} is economic development. In line with the proposed inverted U-shaped relationship, the coefficients of level of economic development and its square are expected to have positive and negative signs, respectively. Due to data availability, this study uses country-level data so our baseline estimation equation, derived from Equation (1), can be expressed as follows:

$$I_{it} = \varphi_0 + \varphi_1 GDP_{it} + \varphi_2 GDP_{it}^2 + \varphi_3 FD_{it} + \varphi_4 FD_{it}^2 + Z_{it} + \varepsilon_{it} \tag{2}$$

where *i* and *t* denote country and year, respectively; φ are the coefficients; and ε is the classical residual term. Under the Kuznets curve hypothesis, it is assumed that $\varphi_1 > 0$, y $\varphi_2 < 0$, as well as its financial development. All variables are expressed in natural base logarithms to straighten out exponential growth patterns and reduce heteroskedasticity (i.e., to stabilize variance). Finally, Z_{it} is added, which is a vector representing the control variables suggested in previous studies as determinants of *GINI*.

3.2 | Data

This study uses a balanced panel sample of 116 countries worldwide over the period 1985–2018. The list of countries in the sample is shown in Table A1 in the Appendix A. One of the reasons for limiting our sample to 116 countries was the availability of reliable data on the indicators used. Table 1 shows the

TABLE 1 Descriptive statistics of the variables and statistical resources

Variable type	Variable name	Symbols	Variable definitions (measurement)	Source
Explained variable (dependent variable)	Gini coefficient	*GINI1*	Gini coefficient before taxes and transfers	Solt (2020). The Standardized World Income Inequality Database (SWIID)
	Gini coefficient	*GINI2*	Gini coefficient after taxes and transfers	Solt (2020). The Standardized World Income Inequality Database (SWIID)
Explanatory variable (independent variable)	Economic growth	*GDP*	GDP per capita at constant 2010 prices	WDI (2020)
Variable controls	Financial development	*FD*	Financial development Index	IMF (2021)
	Urbanization	*URB*	Total urban population	WDI (2020)
	Globalization	GI	Globalization index	KOF (2021)
	Exports	EID	Export diversification index	IMF (2021)

TABLE 2 Descriptive statistics and correlations

Variables	lnGINI1	lnGINI2	lnGDP	lnFD	lnGI	lnURB	lnEID
Mean	3.810	3.612	8.509	−1.406	4.105	15.614	1.053
Media	3.817	3.637	8.439	−1.363	4.069	15.491	1.073
Max.	4.280	4.209	11.625	0.001	6.596	20.529	2.056
Min.	3.086	2.663	5.101	−5.772	1.179	9.947	−0.240
SD	0.152	0.242	1.513	0.770	0.553	1.680	0.378
Skewness	−0.421	−0.242	0.026	−0.331	1.915	0.081	−0.119
Kurtosis	6.035	2.700	2.032	3.079	9.806	3.485	2.297

statistical information used in this research, which came from four different databases. First, the Gini coefficient before taxes and transfers (GINI1) and after taxes and transfers (GINI2) were taken from data published in The Standardized World Income Inequality Database (SWIID) (2019) version 9.1.

Gross domestic product (GDP) per capita and urbanization (URB) are taken from the World Development Indicators (WDI) of the World Bank (2020), whereas financial development (*FD*) and export diversification (*ED*) are taken from the Financial Development Database and Export Diversification Database, presented by the International Monetary Fund (IMF) (2021). Finally, the globalization index (*GI*) is taken from the KOF globalization index produced by the Swiss Federal Institute of Technology (Dreher, 2006). This index takes values between 0 and 100, with higher values suggesting greater globalization, that is, a greater presence of certain economies in the rest of the countries. In the econometric regressions, the dependent variables were *GINI*1 and *GINI*2, while for the independent variables, GDP per capita was considered a proxy for economic development and (*FD*) for financial development, for the validation of both variables with the Kuznets hypothesis. Meanwhile, the variables *URB*, *GI*, and *EID* are considered control variables. Therefore, Table 2 summarizes the descriptive statistics and the correlation matrix of the variables used in the model.

3.3 | Preliminary tests

Before proceeding to the spatial analysis, some preliminary tests of the variables will be carried out; cross-dependency test (Pesaran, 2004), unit root test (Breitung, 2001; Maddala & Wu, 1999; Pesaran, 2007), and cointegration test (Westerlund & Edgerton, 2008) to ensure that the models were correctly specified. Since according to the theory of cointegration which establishes that, as long as there is cointegration between the dependent and independent variables, these variables can be used to develop a model. See Table A2 to A4 for more details.

3.3.1 | Global Moran's I

The existence of spatial autocorrelation for *GINI*1 and *GINI*2 is verified by Global Moran's I and its formula is measured as follows:

$$\text{Global Moran's I} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{i,j}\left(GINI_{i,t} - \overline{GINI_t}\right)\left(GINI_{j,t} - \overline{GINI_t}\right)}{\left[\frac{1}{N}\sum_{i}^{N}\left(GINI_{i,t} - \overline{GINI_t}\right)^2 \sum_{i=1}^{N}\sum_{j=1}^{N} W_{i,j}\right]} \tag{3}$$

where *W* indicates the spatial weights matrix; more specifically a "queen" type matrix, which considers if country *i* and *j* are adjacent, $W_{i,j} = 1$ and nonadjacent 0. *N* represents the total number of countries in this study. $\overline{GINI}$ represents the mean value of *GINI*1 or *GINI*2. The Global Moran's I range is $(-1, 1)$. When Global Moran's I > 0, it means that *GINI* has a positive spatial correlation. If Global Moran's I < 0, it indicates that the negative correlation is stronger in the spatial distribution. When Global Moran's I $= 0$, *GINI* are spatially expressed as independent or random distributions (LeSage & Pace, 2010; LeSage & Pace, 2014).

TABLE 3 Global Moran's I test for GINI1 and GINI2

Year	Moran's I GINI1	Moran's I GINI2	Year	Moran's I GINI1	Moran's I GINI2
1985	0.571***	0.825***	2002	0.322***	0.810***
1986	0.565***	0.833***	2003	0.307***	0.802***
1987	0.553***	0.841***	2004	0.290***	0.792***
1988	0.534***	0.846***	2005	0.286***	0.787***
1989	0.526***	0.845***	2006	0.287***	0.783***
1990	0.513***	0.844***	2007	0.285***	0.778***
1991	0.495***	0.837***	2008	0.284***	0.771***
1992	0.462***	0.826***	2009	0.286***	0.768***
1993	0.434***	0.814***	2010	0.290***	0.765***
1994	0.410***	0.804***	2011	0.301***	0.758***
1995	0.394***	0.801***	2012	0.319***	0.756***
1996	0.386***	0.809***	2013	0.313***	0.754***
1997	0.377***	0.813***	2014	0.319***	0.754***
1998	0.369***	0.817***	2015	0.327***	0.752***
1999	0.357***	0.818***	2016	0.327***	0.746***
2000	0.347***	0.816***	2017	0.330***	0.743***
2001	0.334***	0.813***	2018	0.328***	0.736***
			Average	0.382***	0.766***

Note: *** denotes significance at the 0.1% level, respectively. The null hypothesis is no global spatial autocorrelation.

3.3.2 | Spatial econometric specifications

According to Elhorst (2012), three basic spatial panel data models are mainly applied to determine spatial correlation, such as the spatial lag panel model (*SLM*), the spatial error panel model (*SEM*) and the spatial Durbin panel model (*SDM*). The *SLM* assumes that the spatially weighted mean *GINI* of neighbors partially constrains the value of an observed *GINI* in a city *i* due to spatial interaction (spillover effect). The *SLM* model is expressed as:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j} y_{i,t} + \beta X_{i,t} + \mu_i + \varepsilon_{i,t} \qquad i = 1,\ldots,N,\ t = 1,\ldots,t \tag{4}$$

where y_{it} represents *GINI*1 or *GINI*2 of country *i* at time *t*; $\rho \sum_{j=1}^{N} w_{i,j} y_{i,t}$ represents the endogenous interaction effects of y_{it}; *X* is a matrix ($NT \times M$) of the explanatory variables assuming there are m variables; ρ represents the spatial autoregression coefficient, which shows the influences of the contemporary spatial correlation between a country and other geographically close or neighboring countries; $yw_{i,j}$ is a spatial element of the spatial weighting matrix ($N \times N$), which is defined as the spatial weights matrix in this study. As in other studies such as Jin et al. (2020) and Long et al. (2020), spatial spillover effects were explored by normalizing the rows, which are an average of all the adjacent cities. The term μ_i represents a spatial unit with a specific individual. $\varepsilon_{i,t}$ is an $(NT \times 1)$, which represents the error term. It must be unrestricted and equivalently distributed with zero mean and variance $(0,\sigma^2)$.

The spatial error model (SEM) incorporates spatial relationships through spatial dependence between error terms that are associated with local and adjacent cities (Ren et al., 2020). SEM is defined as:

$$y_{i,t} = \beta X_{i,t} + \mu_i + \varphi_{i,t} \qquad \varphi_{i,t} = \lambda' \sum_{j=1}^{N} w_{i,j} \varphi_{i,j} + \varepsilon_{i,t} \tag{5}$$

where $\varphi_{i,t}$ represents the spatial autocorrelation error term. λ' is the spatial autocorrelation coefficient term. The other parameters are the same as above. It should be noted that the difference between parameter ρ and λ' is mainly distinguished by the spatial dependence part that is applied in the regression equation.

LeSage and Pace (2009) introduced an equation that encompassed spatially lagged terms of both the dependent and independent variables, taking advantage of the complementary advantages of SLM and SEM, called SDM. SDM can be expressed as:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,t} y_{i,t} + \beta X_{i,t} + \mu_{it} + \sum_{j=1}^{N} w_{i,j} X_{j,t} \gamma + \varepsilon_{i,t} \tag{6}$$

where γ is a vector $(M \times 1)$ of spatial autocorrelation coefficient in relation to the explanatory variables.

However, in the *SDM* regression model, the coefficients of the independent variables cannot reflect the marginal effect accurately.

Therefore, it is misleading to interpret the coefficients as the partial derivatives of the dependent variable with respect to the independent variables, since the coefficients also have spatial interaction effects. Therefore, the correct marginal effect analysis is to rewrite the *SDM* with respect to each cross section.

$$E(Y)_t = (I-\rho W)^{-1}\mu + (I_n-\rho W)^{-1} + (X_t\beta + WX_t\gamma), \tag{7}$$

where I_n is an identity matrix $(n \times n)$ and the spatial multiplier matrix $(I_n-\rho W)^{-1}$ is equal to: $(I_n-\rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \rho^4 W^4 + \dots$. Thus, at a specific moment of t, with respect to the kth explanatory variable, the matrix of partial derivatives of the dependent variable in the different units is:

$$\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdots \frac{\partial E(Y)}{\partial x_{Nk}}\right] = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix}_t = (I_n-\rho W)^{-1} \begin{bmatrix} \beta_k & W_{12}\gamma_k & \cdots & W_{1n}\gamma_k \\ W_{21}\gamma_k & \beta_k & \cdots & W_{2n}\gamma_k \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}\gamma_k & W_{n2}\gamma_k & \cdots & \beta_k \end{bmatrix}$$

The above matrix can be symbolized by $S = \frac{\partial E(Y)}{\partial x_k} = (I_n-\rho W)^{-1}C$.

Therefore, the average direct effect on Y of a unit change in x_k can be obtained as the average of the diagonal elements of the S matrix. Mathematically, it can be denoted as:

$$\overline{\mathrm{M}}(\mathrm{k})\mathrm{direct} = \frac{1}{n}\sum_{ij}^{n}\frac{\partial E(y_i)}{\partial x_{ki}} = \frac{1}{n}\mathrm{trace}\left[(I_n-\rho W)^{-1}1_n\beta\right] \tag{8}$$

The mean of the total effects can be calculated by averaging over all countries the sum of the rows or columns of the S matrix. Mathematically, it can be denoted as:

$$\overline{M}(k)\mathrm{total} = \frac{1}{n}\sum_{ij}^{n}\frac{\partial E(y_i)}{\partial x_{ki}} = \frac{1}{n}1_n\left[(I_n-\rho W)^{-1}\mathrm{C}\right]1_n \tag{9}$$

The average indirect impacts are also estimated as a difference between the total and direct impacts. Mathematically, it can be denoted as:

$$\overline{\mathrm{M}}(\mathrm{k})\text{indirect effect} = \overline{\mathrm{M}}(\mathrm{k})\text{ total effect} - \overline{\mathrm{M}}(\mathrm{k})\text{direct effect} \tag{10}$$

In order to decide which model best fits the data, we follow the specification tests outlined by Elhorst (2012). First, we estimate traditional panel data models and apply the likelihood ratio (LR) test to examine fixed effects. Next, we use the Lagrange multiplier (LMLAG and LMERR) and robustness (Robust-LMLAG and Robust-LMERR) tests to examine whether the SLM or the SEM is more appropriate to describe the data than a model without spatial interaction effects.

4 | EMPIRICAL RESULTS

Once it is determined that the dependent and independent variables are cointegrated, that is, these variables can be used to build a model (see Tables A2 to A4). We proceed to use Moran's I index to check the degree of spatial autocorrelation. A positive and statistically significant value of Moran's I indicates spatial clustering and a negative value of this index indicates spatial dispersion in the sample countries (Anselin et al., 1996). By using *GINI*1 and *GINI*2 data from 95 countries, Moran's I index is calculated for each year from 1985 to 2018, as well as the average value for the study period. These results are shown in Table 3, which indicate that Moran's I index is positive and is statistically significant at the 0.1% level. This means that both *GINI*1 and *GINI*2 of the world economies have a significant positive spatial autocorrelation. In addition, the mean indices of 0.382 and 0.766, for *GINI*1 and *GINI*2, respectively, show insignificant changes in Moran's I indices for the rest of the years, that is, the global impact of spatial agglomeration was stable in the two inequality measures throughout the study period. This result is supported by the evidence found by You et al. (2020), showing a positive and significant spatial autocorrelation in a global sample.

Although Moran's I test can show that there are spatial correlations, it also has certain limitations, for example, it can only provide the total mean correlation. However, when a positive spatial autocorrelation is found in certain countries and a negative spatial autocorrelation is found in others, the effects can cancel each other out (LeSage & Pace, 2014). Therefore, Moran's I index becomes zero and does not show any spatial autocorrelation (Espoir & Ngepah, 2021).

In this regard, a Moran scatter plot analysis is used to test for spatial dependence. Due to the complexity of covering the entire study period individually, data for the years 1985, 1995, 2005, 2015, and 2018 are used to show Moran's I scatter plot graphs of the *GINI*1 and *GINI*2 index, which are shown in Figure 1. Each point in the figure denotes a country's *GINI*1 and *GINI*2. The diagonal line in the figure is the regression line of the global Moran test and its slope is the test statistic.

In quadrants one and three, the observations in Moran's I scatter plot have spatial clustering characteristics, meaning that countries with similar characteristics are located next to each other. However, the observations in quadrants two and four have spatial heterogeneity, suggesting that their characteristics are different from those of their surroundings. Therefore, Figure 1 shows that the countries are mainly located in the first and third quadrants with respect to *GINI*2, with relatively few countries in the second and fourth quadrants, whereas for *GINI*1 there is a greater presence in the second and fourth quadrants. Thus, these results show that global *GINI*1 and *GINI*2 are characterized by spatial heterogeneity, as well as by spatial clustering, with the dominant feature being spatial clustering in *GINI*2. Thus, these results show that global *GINI*1 and *GINI*2 are characterized by spatial heterogeneity, as well as by spatial clustering, with spatial clustering in *GINI*2 being the dominant feature. Therefore, world income inequality differs not only in its degree of presence, but also in

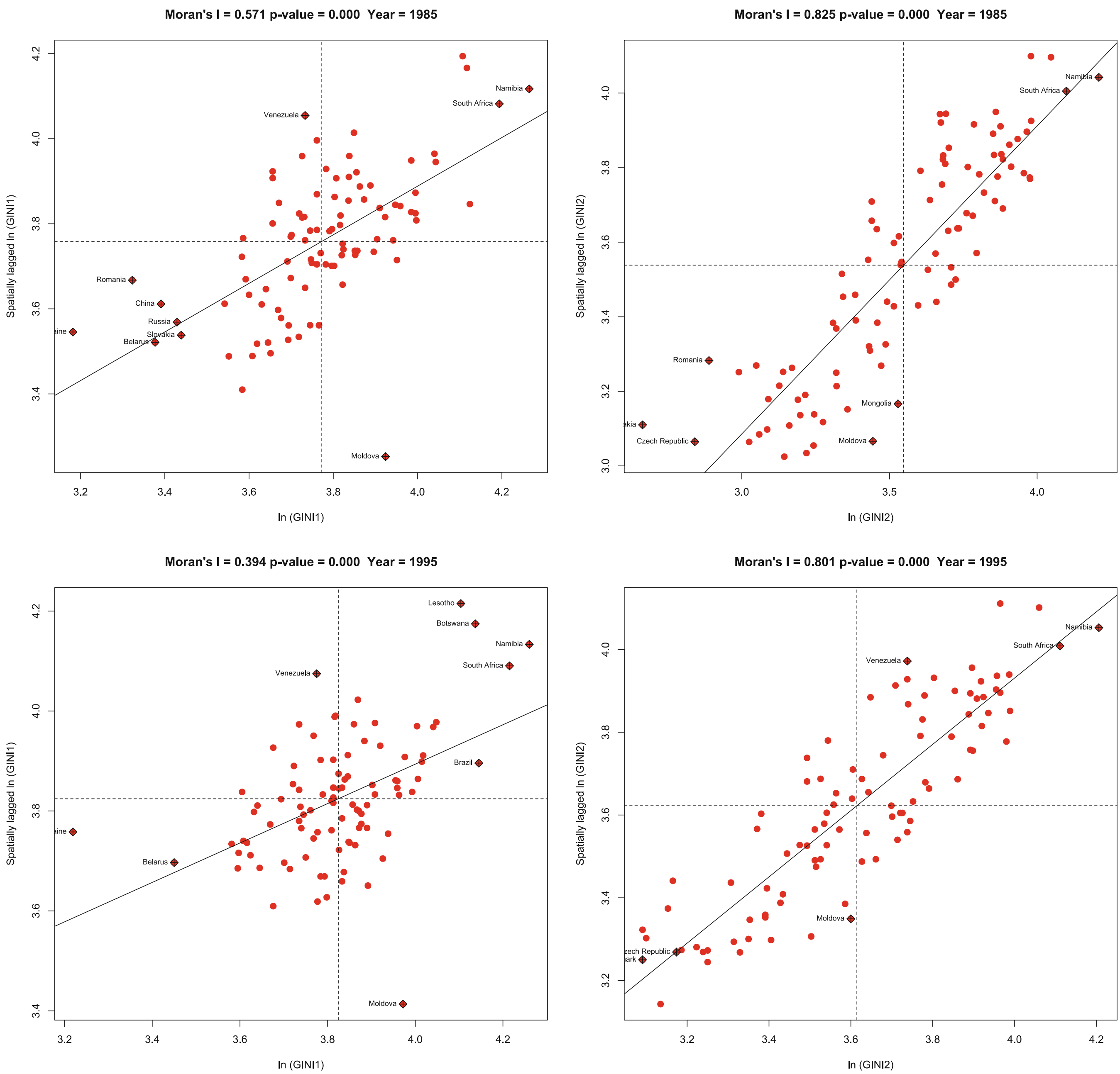

FIGURE 1 GINI1 and GINI2 Moran's I scatter plot [Colour figure can be viewed at wileyonlinelibrary.com]

relation to the inequality correlation between adjacent countries. Furthermore, countries with similar levels of inequality tend to form a cluster with neighboring countries with the same level of inequality. This inequality behavior resembles that found by Panzera and Postiglione (2021) in 245 EU NUTS-2[1] and by Barros and Gupta (2017) in the provinces of South Africa.

Along with the spatial distribution of *GINI*1 and *GINI*2 in Figure 2, we can conclude, in continuity, that countries with the same levels of inequality tend to cluster together, especially those with similar values, with clustering in *GINI*2 being more significant. As a result, we proceed to examine spatial econometric models and select the appropriate model for the analysis. Hence, the statistical significance of Moran's I-index values suggests that general econometric methods that do not compensate for spatial dependence may produce possibly biased estimators (You & Lv, 2018).

Similarly, to further observe the previous statements, Figure 3 shows the Local Indicator of Spatial Association (LISA) cluster of *GINI*1 and *GINI*2. These show that high income inequality countries are close to countries with high income inequality, while economies with low income inequality are neighbors to economies with low income inequality. Consequently, we test whether spatial econometric models are better than general econometric models and the appropriate model is chosen to analyze the impact factors of *GINI*1 and *GINI*2 in the following steps.

In order to determine which model is more appropriate, following Elhorst (2012), we run the models without spatial interaction effects and

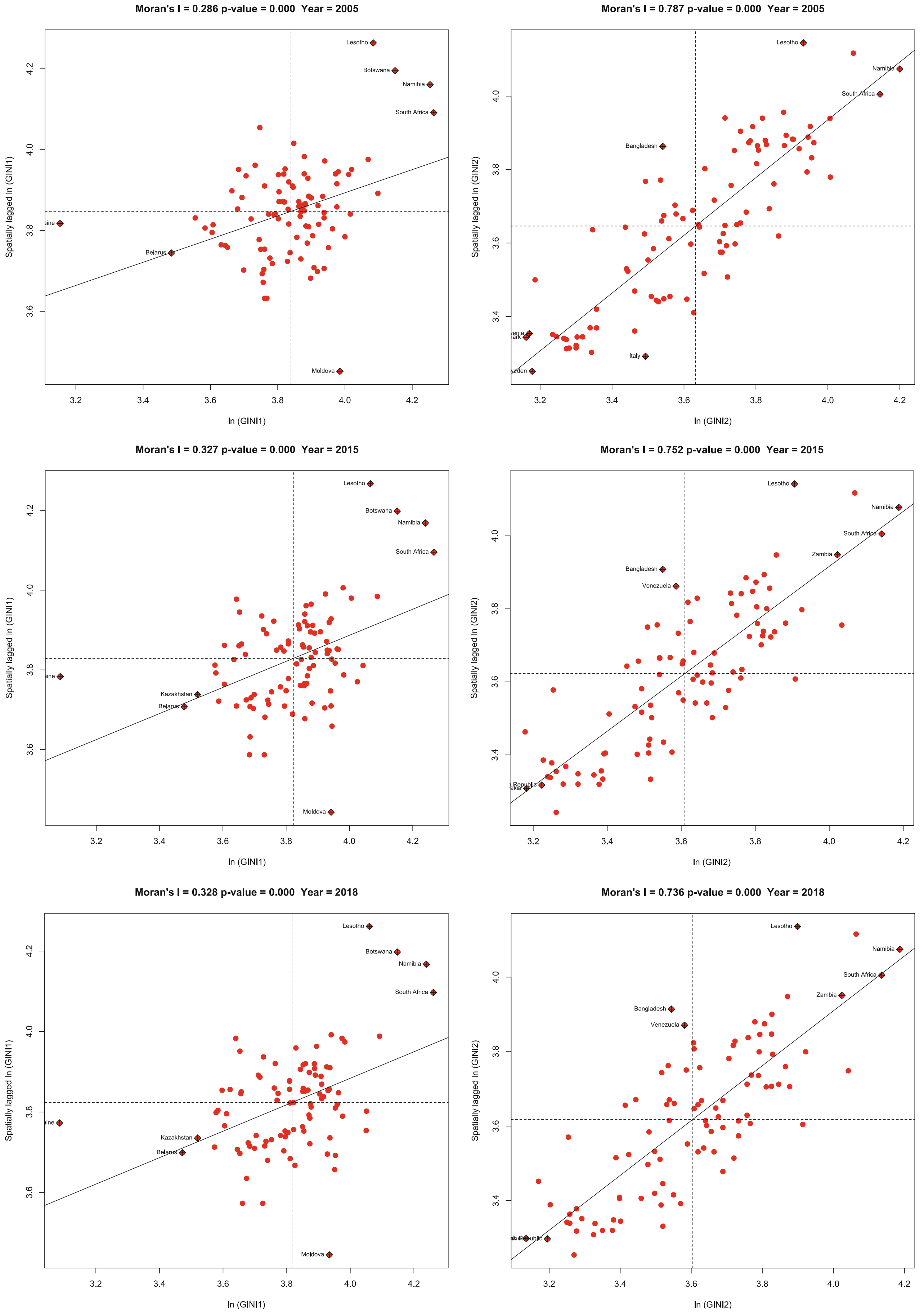

FIGURE 1 (Continued)

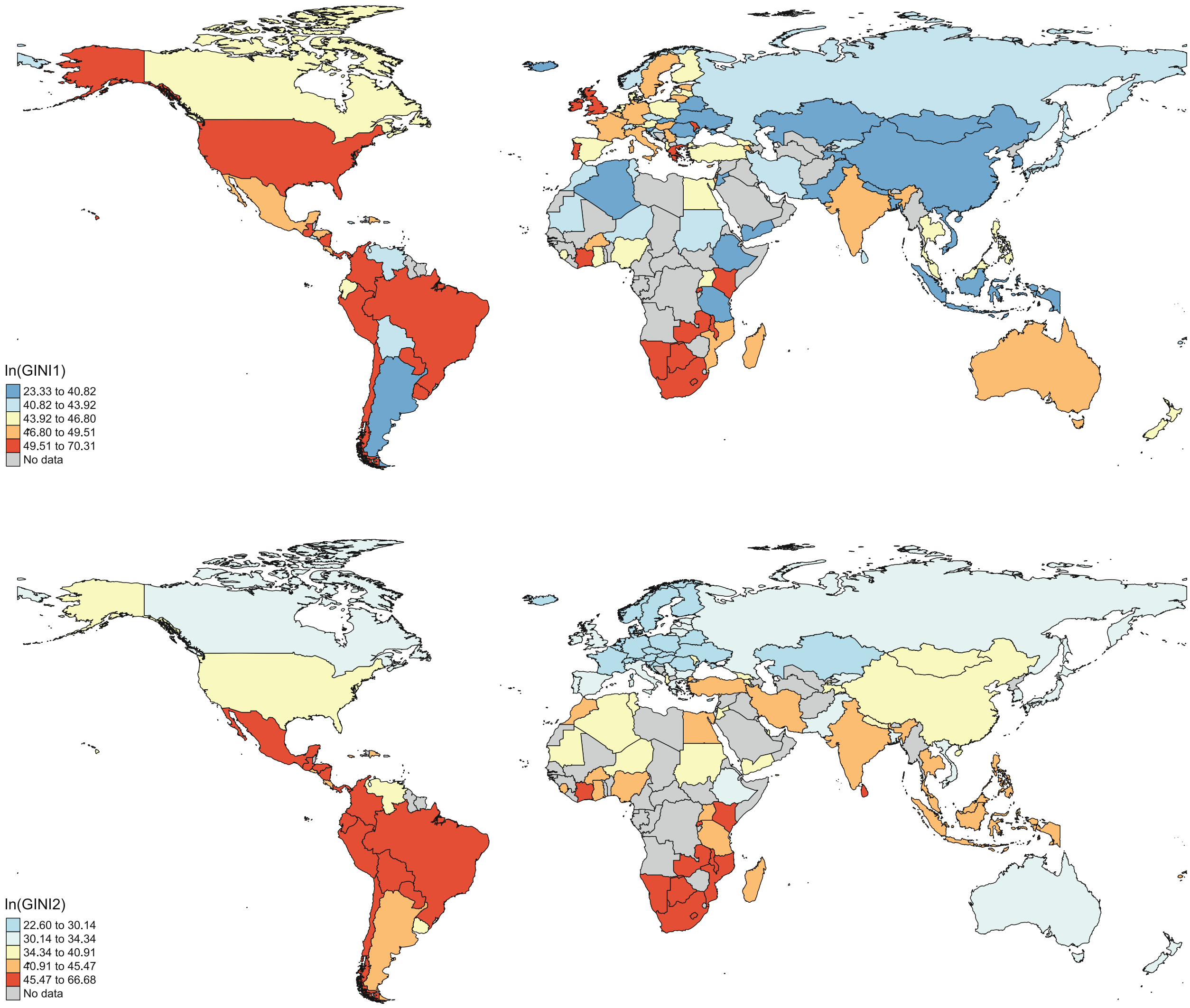

FIGURE 2 Spatial distribution of GINI1 and GINI2. The class breaks correspond to quantiles of the distribution of the variable for each year. The arithmetic average (1985 to 2018) of natural log of GINI1 and GINI2 are used [Colour figure can be viewed at wileyonlinelibrary.com]

perform the corresponding LM lag (Lagrange Multiplier) and LM error tests, and their robust versions, to examine whether the nonspatial panel data models ignore the spatial interaction effects of the data or not. Tables 4 and 5 show the estimation results of the nonspatial panel data models, both for *GINI*1 and *GINI*2, respectively. These results show a clear convex relationship between GDP per capita and income inequality, even when controlling for additional regressors for both *GINI*1 and *GINI*2.

For the LM tests, the null hypothesis that the dependent variable is not spatially lagged and the null hypothesis that the error term is not spatially autocorrelated are strongly rejected at the 1% significance level in all specifications for *GINI*1 and *GINI*2.

Regarding the results of the robust versions of the LM tests, the null hypothesis that the dependent variable is not spatially lagged can be rejected at the 1% level of significance in all specifications of the *GINI*1 and *GINI*2 models, while the null hypothesis that the dependent variable of the error term is not spatially autocorrelated cannot be rejected in both specifications. Apparently, these results imply that there is spatial dependence between the data, which is consistent with Moran's I index results. On the other hand, it can be seen that R^2 has a better fit when using *GINI*2 as a dependent variable, as well as when adding the rest of the study variables. Finally, the Log-likelihood shows a better goodness of fit by adding all the regressors to each of the models.

Next, the results of the *SLM* and *SDM* models for both *GINI*1 and *GINI*2 are shown in Table 5. The Hausman test found that there is a random effects *SLM* model for *GINI*1 (9.29, $p = .3118$) and a fixed effects *SLM* model for *GINI*2 (37.86, $p = .000$). These results show that the spatial autocorrelation parameter ρ is statistically significant at 0.1%, which indicates the existence of spatial autocorrelation in the observations. Therefore, this spatial autocorrelation responds to a spatial lag process, that is, income inequality in a country can be

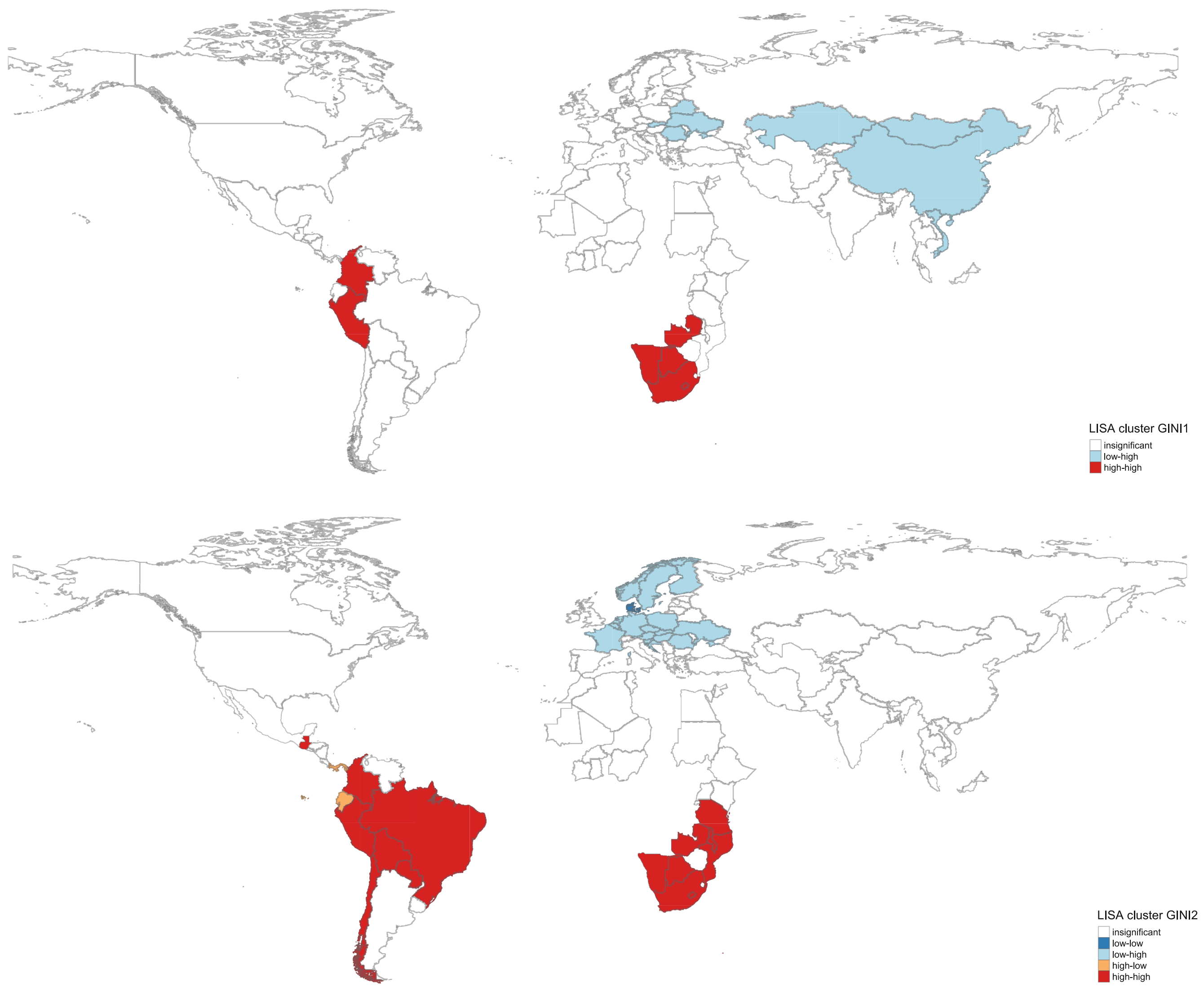

FIGURE 3 The local indicators of spatial association (LISA) cluster maps of GINI1 and GINI2. The arithmetic average (1985 to 2018) of natural log of GINI1 and GINI2 are used [Colour figure can be viewed at wileyonlinelibrary.com]

influenced by inequality in neighboring economies (Achten & Lessmann, 2020; Anselin & Bera, 1998; Puškárová & Vašková, 2021). Furthermore, the *SDM* is applied to investigate the factors that affect both *GINI*1 and *GINI*2. This model was proposed by LeSage and Pace (2009), which contains both the dependent variable and the spatially lagged independent variables, and not only takes the spatial dependence of the explained variable into account, but also that of the explanatory variables.

The results of the Durbin spatial model are shown in Table 5. It is noteworthy that the spatial autocorrelation parameter ρ is statistically significant at the 0.1% level, indicating the existence of spatial dependence in the data. Therefore, the results suggest that an increase in inequality in neighboring countries would lead to an increase in inequality in a country. First, for *GINI*1, the *SDM* model with random effects according to the Hausman test (13.44, $p = .568$), reports a U-shaped fit for economic development, which is the opposite to Kuznets' theory. On the other hand, the results of *GINI*2, according to the fixed effects *SDM* model, chosen from the Hausman test (41.76, $p = .000$), have the same fit as in *GINI*1. In a similar global sample, although regional inequality decreases with increasing GDP per capita, regional polarization is more persistent and does not necessarily follow the same rule (Eva et al., 2022). However, other regional studies contradict the results found in this study, such as the one presented by: Artelaris (2021) in Greece; Blanco and Ram (2019) in the United States, and Pede et al. (2018) in the Philippines. Despite this, Marchand et al. (2020) suggest that differences in the level of economic development between Canadian regions boost these regional patterns of inequality.

Similarly, for financial development, there is no significant adjustment to support a financial Kuznets hypothesis, both with

TABLE 4 Panel estimates for GINI1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln (GDP/pop)	0.099***	0.104***	0.132***	0.102***	0.123***	0.105***	0.131***	0.212***
	(4.877)	(5.195)	(6.159)	(5.004)	(6.089)	(5.213)	(6.489)	(10.043)
ln $(GDP/pop)^2$	−0.004***	−0.006***	−0.008***	−0.005***	−0.006***	−0.005***	−0.006***	−0.013***
	(−4.183)	(−5.301)	(−6.345)	(−4.487)	(−5.258)	(−4.021)	(−5.499)	(−10.416)
ln (FD)		0.043***	0.095***					0.184***
		(7.463)	(6.208)					(11.581)
ln $(FD)^2$			0.014***					0.025***
			(3.666)					(6.877)
ln (GI)				0.018***			0.025***	0.009
				(2.999)			(4.234)	(1.650)
ln (URB)					−0.017***		−0.016***	−0.030***
					(−8.893)		(−8.351)	(−14.408)
ln (EID)						0.060***	0.050***	0.065***
						(6.551)	(5.354)	(7.311)
Constante	3.348***	3.462***	3.412***	3.280***	3.504***	3.217***	3.293***	3.584***
	(39.434)	(40.460)	(39.425)	(37.354)	(40.884)	(37.095)	(36.270)	(39.039)
Observaciones	3230	3230	3230	3230	3230	3230	3230	3230
R^2	.023	.039	.044	.026	.046	.036	.059	.121
Adj.R^2	.022	.039	.043	.025	.045	.035	.058	.119
σ^2	0.025	0.025	0.025	0.025	0.024	0.025	0.024	0.022
Durbin–Watson	2.206	2.204	2.197	2.207	2.273	2.237	2.301	2.352
Log-likelihood	1351.1	1378.7	1385.4	1355.6	1390.2	1372.4	1412.7	1521.9
LM spatial lag	679.64***	680.349***	687.57***	670.94***	640.67***	609.54***	571.79***	550.97***
LM spatial error	731.899***	771.60***	794.33***	17.85***	610.40***	621.15***	491.86***	527.81***
Robust LM spatial lag	88.647***	105.63***	106.48***	7.34***	36.69***	11.61**	129.78***	23.781***
Robust LM spatial error	140.898***	196.92***	213.242***	50.00***	6.42*	0.000	49.848***	0.623

Note: ***, **, and * denote a significance of 0.1%, 1%, and 5%, respectively.

*GINI*1 and *GINI*2. Meanwhile, the globalization coefficient is significant at the 0.1% level. This indicates that increased globalization of neighboring economies would contribute to the increase in the inequality in an economy. Thus, the statement proposed by Engler and Weisstanner (2020) with the so-called "losers of globalization" is reaffirmed in this study. It is possibly linked to the size of the channels that certain developed economies have, channels that do not favor low-income economies, due to their low or nonexistent bilateral relations. On the other hand, the urbanization coefficient is significant at 0.1%, that is, a larger urban population in neighboring economies is associated with a decrease in inequality in an economy. This is related to manufacturing activities, where according to Ragoubi and El Harbi (2018), this sector allows to increase productivity levels and improve the income levels of the population, managing to favorably decrease inequality levels in a given region. Finally, export diversification does not significantly affect *GINI*1, while the effect with *GINI*2 becomes significant. This effect turns out to be the opposite when observing the evidence presented by Fawaz and Rahnama-Moghadamm (2019), who claim that the complexity of an economy, together with exports, are important factors in reducing inequality.

It is noteworthy that the coefficients of the *SDM* model do not directly reflect the marginal effects of the explanatory variables on the dependent variable (LeSage & Pace, 2010), so we report the direct, indirect and total effects of the independent variables shown in Table 6. In this study, the direct effect represents an impact, due to changes in the independent variable(s) on the dependent variables for both *GINI*1 and *GINI*2 in a particular country. The indirect effect represents an impact due to changes in the independent variable, elsewhere, on local income inequality. The total effect is simply the sum of the direct and indirect effects.

In relation to the results, these provide interesting findings. In the case of GDP per capita, the initial effect of the growth of neighboring economies affects the inequality of a local country negatively, both with *GINI*1 and *GINI*2. However, its quadratic version shows an increase in local inequality as growth in neighboring economies increases. Despite attempts to reduce inequality levels, the spillover effect caused by economic growth in its quadratic version does not

TABLE 5 Panel estimates for GINI2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln (GDP/pop)	0.377***	0.388***	0.412***	0.383***	0.366***	0.400***	0.388***	0.465***
	(13.973)	(14.697)	(14.611)	(14.266)	(13.454)	(15.577)	(15.158)	(17.229)
ln (GDP/pop)^2	−0.027***	−0.030***	−0.031***	−0.028***	−0.027***	−0.026***	−0.026***	−0.033***
	(−17.275)	(−19.215)	(−18.522)	(−17.875)	(−16.815)	(−17.642)	(−17.571)	(−20.268)
ln (FD)		0.089***	0.134***					0.186***
		(11.749)	(6.632)					(9.159)
ln (FD)^2			0.012***					0.018***
			(2.385)					(4.008)
ln (GI)				0.046***			0.050***	0.031***
				(5.718)			(6.502)	(4.105)
ln (URB)					−0.008**		0.014***	−0.003
					(−3.032)		(5.754)	(−1.058)
ln (EID)						0.218***	0.233***	0.253***
						(18.695)	(19.963)	(22.125)
Constante	2.431***	2.666***	2.623***	2.259***	2.360***	1.954***	1.606***	2.021***
	(21.556)	(23.752)	(23.079)	(19.437)	(20.506)	(17.746)	(13.929)	(17.302)
Observaciones	3230	3230	3230	3230	3230	3230	3230	3230
R^2	.321	.348	.349	.327	.322	.387	.403	.438
Adj.R^2	.320	.347	.348	.326	.321	.386	.402	.437
σ^2	0.044	0.043	0.042	0.044	0.044	0.040	0.039	0.037
Durbin–Watson	2.029	2.083	2.085	2.010	2.027	2.081	2.055	2.114
Log-likelihood	434.00	501.68	504.52	450.29	438.59	600.12	641.52	743.00
LM spatial lag	2348.21***	2333.20***	2343.88***	2355.73***	2357.55***	1993.23***	2000.23***	1970.53***
LM spatial error	2182.73***	2218.77***	2233.09***	2115.82***	2234.72***	1706.88***	1741.54***	1809.55***
Robust LM spatial lag	172.06***	152.85***	152.68***	240.06***	139.69***	286.64**	259.24***	192.09***
Robust LM spatial error	6.578***	38.42***	41.89***	0.1488	16.86***	0.282	0.55	31.11***

Note: ***, **, and * denote a significance of 0.1%, 1%, and 5%, respectively.

decrease in neighboring regions. This is supported by Crespo and Hernandez (2020), who argue that the most unequal areas of Chile converge with more affluent neighborhoods that also have the highest level of education.

A similar result is obtained with financial development, where the initial spillover effects affect *GINI2* negatively and significantly, that is, the spillover effect amounts to 0.056, while the quadratic version has a positive effect, but not significant in its quadratic version. The favorable effect of financial activities on inequality is mainly linked to the size of the sector and the credit coverage it provides in emerging regions (He et al., 2019). However, uncontrolled and unsupervised growth of this sector could lead to concentration in certain regions, which would have the opposite effect on inequality to that expected (Jung & Cha, 2021). Likewise, Samuel Moon Jung and Vijverberg (2019) suggest that other elements of the financial sector, that is, complementary interlinking activities of banks, are the ones that show a significant influence on inequality reduction.

On the other hand, the spillover effect from globalization is maintained in such a way that it increases the inequality levels in neighboring countries. This is supported by the evidence found by Ezcurra and Del Villar (2021), where the regressive spatial impact of real economic flows would significantly widen regional income disparities at the global level. The direct effect shown in *GINI1* would be linked to the return of the impact of globalization within the same region. Heimberger (2020) links economic globalization as an important determinant of the increase in income inequality, but mainly through financial globalization rather than through trade globalization. This globalization is concentrated in certain regions and does not link the rest of the economies, which do not have the structure to be immersed in this globalization channel (Table 7).

As for urbanization, it has a negative and significant spillover effect in both scenarios (*GINI1* and *GINI2*). In addition, it has a direct effect that returns negatively on urbanization, resulting in a total effect with the same symbol and significance. Thus, income inequality is mitigated by urbanization within and indirectly over the rest of neighboring regions, even in conditions where there is no redistribution. This result is consistent with that presented by Ali et al. (2021), which is replicated in all subsamples according to income level. On the

TABLE 6 The estimation results of the spatial panel model

	GINI1			GINI2		
	SLM	SDM fixed effects model	SDM random effects model	SLM	SDM fixed effects model	SDM random effects model
ρ	0.421***	0.383***	0.403***	0.674***	0.688***	0.368***
	(29.06)	(24.86)	(27.24)	(67.56)	(70.34)	(22.99)
ln (GDP/pop)	−0.0544**	0.347***	0.0320	0.328***	0.402***	0.0130
	(−2.86)	(13.48)	(1.40)	(19.02)	(17.65)	(0.46)
ln (GDP/pop)^2	0.00553***	−0.0195***	0.00106	−0.0230***	−0.0263***	0.00166
	(4.76)	(−12.74)	(0.75)	(−21.62)	(−19.45)	(0.95)
ln (FD)	−0.00686	0.217***	0.00131	0.161***	0.188***	−0.0257**
	(−0.98)	(14.59)	(0.18)	(12.33)	(14.25)	(−2.84)
ln (FD)^2	−0.000167	0.0346***	0.00113	0.0230***	0.0269***	−0.00487**
	(−0.12)	(10.40)	(0.81)	(7.62)	(9.12)	(−2.83)
ln (GI)	0.0111*	−0.0192***	−0.0385***	0.0218***	0.00410	−0.00689
	(2.19)	(−3.55)	(−5.57)	(4.37)	(0.85)	(−0.80)
ln (URB)	−0.0278***	−0.0348***	−0.0211***	−0.00257	−0.00935***	−0.0355***
	(−7.67)	(−18.02)	(−3.80)	(−1.52)	(−5.46)	(−4.69)
ln (EID)	0.0181***	−0.0171	0.0215***	0.0692***	0.0384***	0.0187**
	(3.60)	(−1.87)	(4.37)	(8.69)	(4.73)	(3.07)
Constant	2.631***		3.023***			3.093***
	(27.63)		(26.14)			(22.31)
W*ln (GDP/pop)		−0.327***	−0.157***		−0.243***	−0.138***
		(−8.94)	(−4.97)		(−7.45)	(−3.54)
W*ln (GDP/pop)^2		0.0176***	0.00666***		0.0152***	0.00598*
		(8.04)	(3.40)		(7.77)	(2.46)
W*ln (FD)		−0.163***	−0.0193		−0.131***	−0.0303*
		(−7.13)	(−1.88)		(−6.53)	(−2.40)
W*ln (FD)^2		−0.0257***	−0.00271		−0.0134**	−0.000370
		(−4.51)	(−1.25)		(−2.66)	(−0.14)
W*ln (GI)		0.0697***	0.125***		0.0261***	0.162***
		(8.22)	(12.71)		(3.48)	(13.10)
W*ln (URB)		−0.00331	−0.0189**		−0.00625*	−0.0286**
		(−1.16)	(−2.87)		(−2.53)	(−3.25)
W*ln (EID)		0.0640***	−0.0129		0.0838***	−0.0159
		(5.46)	(−1.56)		(7.99)	(−1.52)
Hausman test	9.29 (0.3118)		13.44 (0.568)	37.86 (0.000)	41.76 (0.000)	
Observations	3230	3230	3230	3230	3230	3230
AIC	−10714.1	−4057.1	−10939.6	−3811.9	−4353.8	−9614.5
BIC	−10647.2	−3959.8	−10830.2	−3757.2	−4256.5	−9505.0
R^2	.0421	.252	.128	.444	.544	.00371
Log-likelihood	5368.1	2044.5	5487.8	4721.7	2192.9	4825.2

Note: ***, **, and * denote a significance of 0.1%, 1%, and 5%, respectively.

other hand, the productivity growth associated with urbanization in developed countries is the opposite in developing economies, where nonurban activities such as agriculture and natural resources are at a comparative disadvantage in terms of income (Adams & Klobodu, 2019; Aiyar & Ebeke, 2020; Quito, Sánchez, et al., 2021; Sulemana et al., 2019). Finally, the indirect effect from export diversification is mitigated by the direct effect, resulting in a non-significant total effect. This result is supported by the evidence proposed by Zhu et al. (2020), who consider that the structure of export products would support the reduction of inequality only in regions with a higher urban level. Therefore, the

TABLE 7 Direct, indirect, and total effects

	GINI1			GINI2		
	Direct	Indirect	Total	Direct	Indirect	Total
ln (GDP/pop)	0.0106	−0.215***	−0.204***	−0.0146	−0.217***	−0.232***
	(0.47)	(−5.23)	(−4.51)	(−0.53)	(−4.46)	(−4.54)
ln $(GDP/pop)^2$	0.00209	0.0106***	0.0127***	0.00357*	0.0119***	0.0155***
	(1.47)	(4.13)	(4.46)	(2.07)	(3.90)	(4.83)
ln (FD)	−0.000811	−0.0286	−0.0294	−0.0349***	−0.0568***	−0.0916***
	(−0.11)	(−1.92)	(−1.59)	(−4.08)	(−3.36)	(−4.76)
ln $(FD)^2$	0.000923	−0.00335	−0.00243	−0.00536**	−0.00186	−0.00723
	(0.64)	(−1.08)	(−0.64)	(−3.18)	(−0.53)	(−1.79)
ln (GI)	−0.0214***	0.166***	0.144***	0.0116	0.230***	0.241***
	(−3.40)	(12.94)	(11.02)	(1.48)	(16.16)	(17.67)
ln (URB)	−0.0251***	−0.0422***	−0.0673***	−0.0571***	−0.0518***	−0.109***
	(−4.97)	(−5.18)	(−8.90)	(−6.82)	(−4.73)	(−12.95)
ln (EID)	0.0208***	−0.00661	0.0142	0.0106	−0.0398**	−0.0291
	(3.77)	(−0.53)	(0.91)	(1.56)	(−2.63)	(−1.52)

Note: ***, **, and * denote a significance of 0.1%, 1%, and 5%, respectively.

spillover effect observed in *GINI*2 would be conditioned by the characteristics of neighboring economies.

5 | CONCLUSIONS

Studies on the effect of growth on inequality levels have been conducted in the literature, but the understanding of this relationship at the spatial level remains limited, especially in this era of rapid globalization, in which countries interact more frequently with each other. To provide a better insight into the effects of economic growth and financial development on income inequality, we examine their spillover effects on inequality, using both an SLM and SDM model as the main spatial models. In general, the results indicate that both pre- and post- tax income inequality are spatially correlated in the countries studied. More importantly, the study finds empirical support for the spatial dependence between economic growth, financial development and both measures of inequality. Specifically, a negative effect of both economic growth and financial development was observed in their early stages, while their quadratic versions do not show favorable results that support the traditional and financial Kuznets hypothesis. The latter prevail over the spillover effects of these indicators to produce a highly significant total effect. Thus, the income inequality in an economy depends not only on the country's institutions and policies, but also on the level of growth and financial development of its neighboring countries. This shows that being surrounded by countries with sustainable economic growth and financial development improves income inequality outcomes. However, the nonlinear effect present in the second growth stage would redirect the current mitigation of income inequality.

5.1 | Managerial implications

Based on the results of this study, we can draw some important political implications. First, the mitigation of income inequality is not only mitigated by growth or early stage financial development, but also by the sustainability of financial growth and development in neighboring countries or regions. Therefore, governments and policy makers should focus their efforts on improving the sustainability of financial growth and development to achieve a positive return on inequality levels, more specifically after improving distribution levels from taxes and transfers. This is only possible when redistribution channels are highly efficient to channel both taxes and transfers, so that inequality levels are reduced and more equitable environments are generated. Second, given that urbanization has proven to be a factor that promotes the reduction of income inequality both before and after taxes, efforts to promote urbanization processes with a sustainable and smart approach should become a global priority. To this end, harnessing the benefits of urban growth through early action, effective coordination, and political leadership is a priority.

Third, it has been observed that globalization does not provide benefits in reducing inequality, even generating indirect effects on neighboring economies that increase income inequality. This means that long-term policies related to multilateral agreements could reverse these undesirable effects, where there is a greater transfer to less developed economies rather than the opposite. Finally, the results shown in relation to export diversification show that it is important to improve export diversification, especially in economies where their main export products are based on the primary sector. This work is not without limitations. The weak point has to do with the scope of the data where not all economies have information on the variables used, which is why it limits the ability of spatial models to generate indirect effects, as they do not find neighborhoods for certain economies. Likewise, the time period was limited to 2018, due to the availability of data especially related to the dependent variables.

Future research could incorporate more empirical components such as corruption or government decentralization that show the nonlinear relationship with income inequality. Furthermore, since freedoms can influence individuals as an advantage or lack of opportunities, depending on the environment. It may be necessary to incorporate it in the future when better data coverage is available at the country level, compared to the current ones. In addition, the more disaggregated use of regions could improve the explanatory power, due to the significant increase in the sample size.

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ENDNOTE

[1] Nomenclature of Statistical Territorial Units of the European Union. 2: basic regions for the application of regional policies.

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APPENDIX A

Table A1

A.1. | Preliminary test on variables

We first begin with a preliminary analysis of the variables by conducting a cross-section dependence (CD) test for each of the variables to further examine the existence of spatial dependence among the study sample (Pesaran, 2004). The results in Table A2 reject the null hypothesis of cross-sectional independence at 0.01%, thus highlighting the importance of considering spatial dependence among the study countries.

Continuing with the analyses, two CADF and CIPS second-generation unit root tests based on Pesaran (2007) are performed. Since these tests produce accurate results in the presence of cross-dependent (CD). The results of both tests are presented in Table A3. These show that, after the first differentiation, all variables are stationary at 0.01% (CADF) and 1% (CIPS). Therefore, it is necessary to prove the cointegration of the set of variables. In addition, they are contrasted with first generation tests such as Breitung (2001) and Maddala and Wu (1999) or better known as IPS.

Third, a panel cointegration test was performed using the long-term cointegration test developed by Westerlund and Edgerton (2008), which, in addition to considering the DC, includes structural breaks, which may be located on different dates for different panel members. In addition, this test allows for heteroskedastic and serially correlated errors as well as unit-specific time trends. The two test statistics $Z_{\varphi}(N)$ y $Z_{\tau}(N)$ from Westerlund and Edgerton (2008) reported in Table A4 reveal evidence in favor of a long-term relationship between the inequality measures and the independent variables, some when allow breaks in the level and others in the slope of this relationship.

TABLE A1 Sampled countries

Country name							
1	Albania	30	Estonia	59	Lesotho	88	Romania
2	Algeria	31	Ethiopia	60	Lithuania	89	Russia
3	Argentina	32	Fiji	61	Luxembourg	90	Rwanda
4	Armenia	33	Finland	62	Madagascar	91	Serbia
5	Australia	34	France	63	Malawi	92	Sierra Leone
6	Austria	35	Gambia	64	Malaysia	93	Singapore
7	Bangladesh	36	Georgia	65	Mauritania	94	Slovakia
8	Barbados	37	Germany	66	Mauritius	95	Slovenia
9	Belarus	38	Ghana	67	Mexico	96	South Africa
10	Belgium	39	Greece	68	Moldova	97	Spain
11	Bolivia	40	Guatemala	69	Mongolia	98	Sri Lanka
12	Botswana	41	Honduras	70	Morocco	99	Sudan
13	Brazil	42	Hungary	71	Mozambique	100	Sweden
14	Bulgaria	43	Iceland	72	Namibia	101	Switzerland
15	Burkina Faso	44	India	73	Nepal	102	Tajikistan
16	Canada	45	Indonesia	74	Netherlands	103	Tanzania
17	Chile	46	Iran	75	New Zealand	104	Thailand
18	China	47	Ireland	76	Nicaragua	105	Tonga
19	Colombia	48	Israel	77	Niger	106	Tunisia
20	Costa Rica	49	Italy	78	Nigeria	107	Turkey
21	Cote d'Ivoire	50	Jamaica	79	Norway	108	Uganda
22	Croatia	51	Japan	80	Pakistan	109	Ukraine
23	Cyprus	52	Jordan	81	Panama	110	United Kingdom
24	Czech Republic	53	Kazakhstan	82	Paraguay	111	United States
25	Denmark	54	Kenya	83	Peru	112	Uruguay
26	Dominican Republic	55	Korea	84	Philippines	113	Venezuela
27	Ecuador	56	Kyrgyzstan	85	Poland	114	Vietnam
28	Egypt	57	Laos	86	Portugal	115	Yemen
29	El Salvador	58	Latvia	87	Qatar	116	Zambia

TABLE A2 Cross-sectional dependence tests and

Variables	lnGINI1	lnGINI2	lnGDP	lnFD	lnGI	lnURB	lnEID
CD-test	58.484***	48.988***	333.084***	202.45***	444.52***	269.441***	13.667***

Note: The CD-test performs the null hypothesis of cross-sectional independence. The test statistical follows the normal standard distribution N (0, 1). *** denotes significant at the .01% level.

TABLE A3 Panel unit root tests

Variable		IPS	Breitung	CADF	CIPS
lnGINI1	Level	2.973 (0.998)	0.796 (0.787)	0.119 (0.547)	−1.642
	Second difference	−53.789*** (0.000)	−9.369*** (0.000)	−20.818*** (0.000)	−6.138
lnGINI2	Level	3.305 (0.999)	0.864 (0.806)	−0.673 (0.750)	−1.637
	Second difference	−50.247*** (0.000)	−11.293*** (0.000)	−21.359*** (0.000)	−6.080
lnGDP	Level	5.406 (1.000)	8.149 (1.000)	−1.407 (0.080)	−2.128
	Second difference	−50.121*** (0.000)	−6.909*** (0.000)	−23.3047*** (0.000)	−6.114
lnURB	Level	1.467 (0.9288)	1.938 (1.000)	−0.347 (0.364)	−2.109
	Second difference	−29.891*** (0.000)	−13.429*** (0.000)	−10.304*** (0.000)	−4.469
lnFD	Level	−2.192* (0.014)	2.574 (0.993)	−3.195** (0.001)	−2.265
	Second difference	−52.357*** (0.000)	−6.995*** (0.000)	−30.293*** (0.000)	−6.153
lnHC	Level	−4.229*** (0.000)	0.366 (0.647)	−0.267 (0.395)	−1.881
	Second difference	−8.052*** (0.000)	−13.2097*** (0.000)	−14.375*** (0.000)	−5.786

Note: ***, **, and * denote a significance of 1%, 5%, and 10%, respectively. The critical values of CIPS in level are −2.04, −2.11, and – 2.23 for 10%, 5%, and l% level, respectively. The critical values of CIPS in the first difference are −2.54, −2.61, and −2.73 for 10%, 5%, and l% level, respectively.

TABLE A4 Westerlund and Edgerton (2008) panel cointegration test with structural breaks results

		$Z_{\varphi}(N)$	$Z_{\tau}(N)$
GINI1	No break	−7.003*** (0.000)	−16.862***(0.000)
	Level shift	−3.883*** (0.000)	−9.241*** (0.000)
	Regime shift	−1.076 (0.141)	−7.012*** (0.000)
GINI2	No break	−24.987***(0.000)	−47.109***(0.000)
	Level shift	−0.139 (0.445)	−3.944*** (0.000)
	Regime shift	−1.194 (0.884)	−1.783* (0.037)

Note: The LM-based test statistics $Z_{\varphi}(N)$ and $Z_{\tau}(N)$ are normal distributed. The number of common factors is determined by means of the information criterion proposed by Bai and Ng (2004) and the maximum number is set to five. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.