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Influence of income inequality and patenting activity on the ecological footprint in Latin America: An analysis of panel data

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Abstract:

This paper studies the influence of income inequality and patenting activity on ecological footprint in selected Latin American countries from 1991 to 2018. In this research, econometric methods of panel data are applied (e.g., the new Moment Quantile Regression Method, the panel-corrected standard error (PCSE), and the fully modified ordinary least squares (FMOLS) method). The results demonstrate that renewable energy and patenting activity reduce environmental degradation while income inequality and economic growth increase it. Therefore, promoting renewable energy, the patenting activity of cleaner technologies, and environmental regulation to reduce environmental degradation are essential. In addition, it is urgent to design and apply income redistribution policies to reduce environmental pressure.

Keywords: panel data, income inequality, ecological footprint, renewable energy consumption, Latin America; patents.
JEL classification: E60, C20, O30, Q40, Q50.

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Resumen

La influencia de la desigualdad de ingresos y la actividad patentadora sobre la huella ecológica en América Latina: un análisis de datos de panel

En este artículo se estudia la influencia de la desigualdad de ingresos y la actividad de patentes en la huella ecológica en los países latinoamericanos seleccionados en el periodo 1991-2018. Se aplican métodos econométricos de datos de panel (entre ellos, el nuevo Método de Regresión cuantil de Momentos, el de Errores Estándar Corregidos para Panel (PCSE, por sus siglas en inglés) y el de Mínimos Cuadrados Ordinarios Totalmente Modificados (FMOLS, por sus siglas en inglés). Los resultados demuestran que la energía renovable y la actividad de patentes reducen la degradación ambiental, mientras que la desigualdad de ingresos y el crecimiento económico la aumentan. Se concluye que el impulso de las energías renovables, la actividad de patentamiento de tecnologías más limpias y la regulación ambiental son esenciales para reducir la degradación ambiental. Además, es urgente diseñar y aplicar políticas de redistribución del ingreso para ayudar a reducir la presión ambiental.

Palabras clave: datos de panel, desigualdad de ingresos, huella ecológica, consumo de energía renovable, América Latina, patentes.

Clasificacion JEL: E60, C20, O30, Q40, Q50,

Introduction

Economic growth and pollution reduction is a major challenge for many countries. In this sense, the Kuznets curve shows a relationship between economic growth and pollution. Indeed, carbon dioxide emissions contribute to global warming and climate change, receiving great attention from governments, international organizations, and environmentalists (Cheng, Ren and Wang, 2019). The use of energy is required for the production of goods and services to satisfy the population´s needs (Gómez and Rodríguez, 2019).

Panayotuo (1993) was among the first scholars to test and validate the inverted U-shaped hypothesis. Other studies with favorable results are Altıntaş and Kassouri (2020), Awad (2022), Chishti and Sinha (2022), Gyamfi *et al.* (2021), Karimi *et al.* (2022), Khan *et al.* (2022), Nizamani *et al.* (2023), Ridzuan (2019), Sesma-Martín and Puente-Ajovín (2022), and Taghvaee *et al.* (2022). In the same way, studies that do not validate this hypothesis are Kalim *et al.* (2023), Minlah and Zhang (2021), and Wang *et al.* (2023). Finally, those that present inconclusive evidence are Aydin *et al.* (2023), Churchill *et al.* (2018), Görmüş and Aydin (2020), and Işık *et al.* (2022).

Carbon dioxide emissions have been widely used. Recently, the ecological footprint per capita is considered the most complete measure of environmental degradation and it has been used in several studies (Altıntaş and Kassouri, 2020; Dogan *et al.,* 2020; Gómez and Rodríguez, 2020). The amount of natural capital needed to sustain resource demand and waste absorption requirements in global hectares of bioproductivity is known as the ecological footprint (Wackernagel *et al.,* 2004). This indicator covers various aspects of environmental degradation, namely agricultural land, carbon, and grazing land footprint, in opposition to conventional greenhouse gas indicators (Altıntaş and Kassouri, 2020). Indeed, the ecological footprint measures more accurately the environmental degradation tracking the use of multiple categories of productive land in opposition to carbon dioxide emissions (Dogan *et al.,* 2020).

Nowadays, renewable energy consumption (Altıntaş and Kassouri, 2020; Cheng, Ren and Wang, 2019; Gómez and Rodríguez, 2020) and income inequality (Ehigiamusoe *et al.,* 2022; Khan *et al.,* 2022) allow explaining environmental degradation. Industrialized countries tend to have relatively stricter environmental standards than the laws of the poorest and middle-income countries (Torras and Boyce, 1998). Nevertheless, poor and powerless individuals in highly unequal societies have less information on environmental impacts based on the propaganda that pollution is worth it (Boyce, 2002). Therefore, as economic and political inequalities are more significant, they generate greater environmental degradation (Boyce, 2008). Societies with more income inequality tend to be less interested in environmental protection (Ridzuan, 2019) because poor countries are more concerned with daily survival and less interested in pursuing environmental policies (Stiglitz, 2014).

The development of patents also reflects the reduction of polluting emissions. Popp (2005) suggests patents offer an advantage when analyzing technology change and environmental effects as they may improve existing technologies that reduce pollution (Cheng, Ren and Wang, 2019). In this regard, Töbelmann and Wendler (2020) studied environmental innovations and carbon dioxide emissions for the EU-27 from 1992-2014, finding that environmental innovations contributed to reducing carbon dioxide emissions in these countries during this period. Gómez and Rodríguez (2020), in the case of the USMCA countries, find a negative relationship between these variables, but it is not statistically significant.

According to Moreno (2020), the Latin American region is one of the regions with the highest inequality in terms of labor income. These authors also suggest that this region's richest population (1%) captures more than 20% of the entire income in Latin American countries. In the same way, these authors point out that the least favored sectors in terms of income have fewer opportunities to grow and develop since they are more exposed to the adverse effects of development, such as climate change. A significant cause explaining these inequalities in the Latin American region lies in many less efficient governments combating these inequalities through income redistribution, public spending, and taxes (Moreno, 2020).

In this sense, this research studies the influence of income inequality and patenting activity on environmental degradation in six selected Latin American countries through a panel data analysis for the period 1991-2018. Among these countries, Chile, Costa Rica, and Mexico show that the ecological footprint exceeded biocapacity, generating a growing ecological deficit in recent years. At the same time, Argentina, Brazil, and Colombia still have an ecological surplus with a clear trend to reduce it (Global Footprint Network, 2022). The research question is: What is the influence of income inequality and patenting activity on environmental degradation in six selected Latin American countries (1991-2018)?

This research contributes to the literature on the Latin American region in the following aspects. First, it is one of the first studies that analyzes the determinants of the ecological footprint in these selected Latin American countries. Secondly, it is also one of the first studies that include variables different from the existing literature as determinants of environmental degradation (e.g., renewable energy, income inequality, and patents) in the analysis. Thirdly, it applies the Quantile Regression Method of Moments with fixed effects proposed by Machado and Santos (2019). In addition to this Introduction, this paper is organized into four sections. Section One briefly describes the materials and methods applied in this paper. Section Two presents the econometric results. Section Three discusses the main achieves in this paper. Finally, Section Four presents some conclusions.

1. Data and Methods

This paper studies the impact of the Gross Domestic Product (GDP), renewable energy consumption (EnerR), income inequality (Gini), and applied patents (Patents) on environmental degradation measured by the ecological footprint (EcolF), with annual data of some selected countries of Latin America from 1991 to 2018. The countries with which data is available are Argentina, Brazil, Chile, Colombia, Costa Rica, and Mexico. The GDP per capita (constant dollars of 2010) and the Patents were taken from the World Bank (http://databank.bancomundial.org/data). We take the Gini index from the Standardized World Income Inequality Database (SWIID) (Solt, 2020). Data on EnerR (% of total final energy consumption) were taken from the Renewable Energy Indicators of the Organization for Economic Cooperation and Development (OECD) (https://data.oecd.org/energy/renewable-energy.htm). In contrast, EcolF was taken over by the Global Footprint Network (https://www.footprintnetwork.org/our-work/).

Table 1
Descriptive statistics

Variable	Observations	Mean	Median	Max.	Min.	J-B	Prob.	Std.
Ecolf	168	2.843	2.850	4.293	1.807	3.743	0.153	0.586
EnerR	168	27.373	30.340	48.938	7.650	13.682	0.001	13.332
Gini	168	47.326	47.150	54.300	37.500	4.002	0.133	4.009
GDP	168	8640.321	8581.610	14200.270	3640.455	3.376	0.184	2699.832
Patents	168	6902.810	3244.500	30884.00	75.000	64.937	0.000	7763.345

Source: own elaboration of the authors based on the sample.

According to the descriptive statistics presented in Table 1, considering the Jarque-Bera test (J-B), all variables are normally distributed except EnerR and Patents. The Ecolf has an average of 2.843 (measured by global hectares per person), with a maximum value of 4.293 and a minimum of 1.807. For its part, EnerR has an average value of 27.373, with a range of

7.650 to 48.938. Concerning the Gini index, it has an average of 47.326, with a range from 37.50 to 48.938. An average GDP of 8640.321, which can vary from 640.455 to 14200.270. Finally, Patents have a minimum value of 74 and a maximum of 30884, with an average value of 6902.

Natural logarithms were applied to the variables used in the following model:

$$EcolF_{it} = \beta_{0it} + \beta_{1i}EnerR_{it} + \beta_{2i}Gini_{it} + \beta_{3i}GDP_{it} + \beta_{4i}Patents_{it} + e_{it} \quad (1)$$

Where *i* indicates the six countries, *t* is the time range of the data period, and e_{it} represents the error term. The parameters β_1, β_2, β_3, β_4, and β_5 represent the long-term elasticity of EnerR, Gini, GDP, and Patents concerning environmental degradation (EcolF), respectively. According to the literature (Altıntaş and Kassouri, 2020; Cheng, Ren and Wang, 2019; Gómez and Rodríguez, 2020), it is expected that an increase in the use of renewable energy decreases environmental damage ($\beta_1 <$ 0). In the same way, greater income inequality leads to greater environmental degradation ($\beta_2 >$ 0) (Ehigiamusoe *et al.,* 2022; Khan *et al.,* 2022). According to Churchill *et al.* (2018) and Gómez and Rodríguez (2020), the GDP coefficient should be positive due to the scale effect ($\beta_3 <$ 0). Finally, developing patents may generate new technologies for reducing polluting emissions ($\beta_4 <$ 0) (Cheng, Ren and Wang, 2019).

To avoid spurious results, it is essential to know the order of variables integration, and if there are conditions for cointegration testing, long-term equilibrium relationships must be checked when working with time series or panel data. Indeed, by combining time series with cross-sectional data, the observation number increases, and the efficiency estimation parameters improve (Baltagi, 1995). In addition, unit root tests on panel data have greater power than unit root tests on time series. According to the characteristics of the data, however, it is essential to test the cross-sectional dependence of variables to apply the most appropriate unit root and cointegration tests (Gómez and Rodríguez, 2020). In this sense, three cross-sectional dependence tests were applied: Breusch-Pagan LM, Bias-corrected scaled LM, and Pesaran CD.

The first-generation panel data unit root tests of Levin *et al.* (2002), Im *et al.* (2003), Fisher-type tests using ADF (ADF-Fisher), and PP (PP-Fisher) (Maddala and Wu, 1999; Choi, 2001) and the second-generation PESCADF test from Pesaran (2007) were applied. The former assumes cross-section independence, while the latter allows cross-section dependence. Due to the possibility of cross-section dependence, the Westerlund (2007) cointegration test is applied. Westerlund's cointegration test: is based on the normal distribution; considers autocorrelation and heteroscedasticity; supports cross-section dependence within or between panel units; it is suitable for small samples; it has high power compared to residual-based cointegration tests. In addition, the Pedroni (1999) and Kao (1999) cointegration tests are applied.

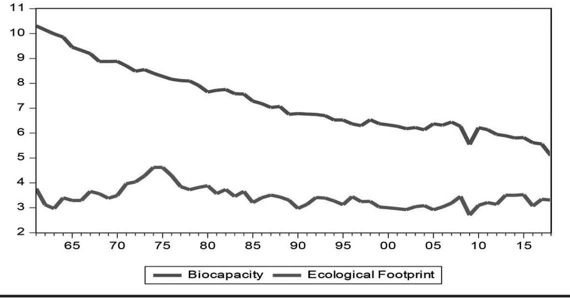
To estimate long-term parameters, some methods have been developed, such as fully modified OLS (FMOLS) and dynamic OLS (DOLS) estimators (Kao and Chiang, 2000; Pedroni, 2001; Phillips and Moon, 1999) that generate asymptotically unbiased and normally distributed coefficient estimators (Phillips and Moon, 1999). In this research, the FMOLS estimator is used since it behaves relatively well, guarantees consistent results, and controls for the endogeneity of the regressors, and the serial correlation (Pedroni, 2001; Phillips and Moon, 1999). In addition, in the presence of cross-dependence, one of the methods used is the panel-corrected standard error (PCSE), which allows a better inference of the estimates with cross-section dependence. However, cross-section dependence and serial correlation present a problem because the most common panel data estimators do not control them simultaneously (Chishti and Sinha, 2022; Reed and Ye, 2011). According to Reed and Ye (2011), two possible solutions are the feasible generalized least squares (FGLS) estimator proposed by Parks (1967) and the PCSE estimator proposed by Beck and Katz (1995). However, according to Reed and Ye (2011), the latter estimator is substantially better than the former. Therefore, FMOLS and PCSE will be used in this research to find more robust results.

Additionally, the Quantile Regression Method of Moments (Machado and Santos, 2019) with fixed effects has the following advantages. First, it estimates more robust results for outliers emanating from the dependent variable (Koenker, 2004). Second, it represents the impact of the independent variables on the dependent in the full distribution (Ike *et al.,* 2020). Therefore, panel quantile regression allows a complete picture of the relationship between variables (Allard, 2018). In the analysis of panel data, it is possible the presence of heterogeneity in the cross-sectional units (Gómez and Rodríguez, 2020). For this reason, we use the Dumitrescu and Hurlin (2012) proposal that tests causality with good statistical properties and cross-section dependence panels.

2. Results

This section presents the results found in this paper. Figures 1-6 show the behavior of the ecological footprint and biocapacity (measured by global hectares per person) for the six selected Latin American countries.

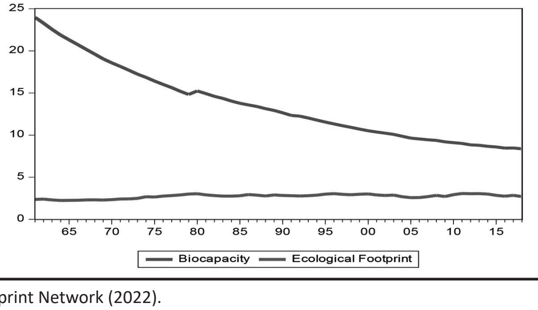
Figure 1
Ecological Indicators (measured by global hectares per person) of Argentina



Source: Global Footprint Network (2022).

Argentina and Brazil (figures 1 and 2) show an ecological footprint lower than their biocapacity per capita (i.e., ecological reserve). However, the ecological reserve in both countries decreases steadily.

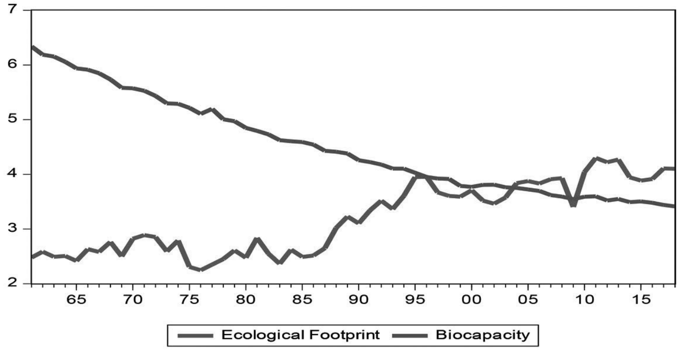
Figure 2
Ecological Indicators (measured by global hectares per person) of Brazil



Source: Global Footprint Network (2022).

Chile (figure 3) shows an ecological deficit since its ecological footprint exceeds its biocapacity since 2004.

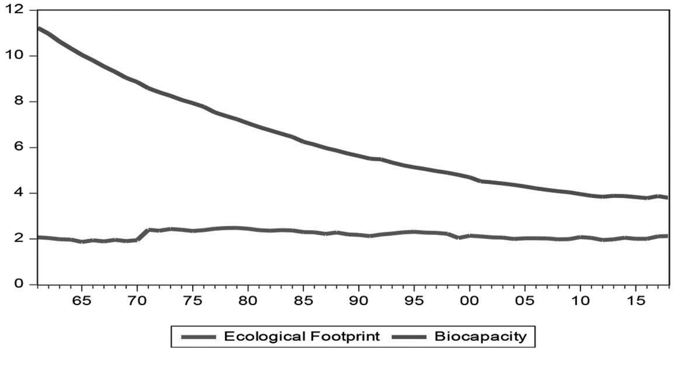
FIGURE 3
ECOLOGICAL INDICATORS (MEASURED BY GLOBAL HECTARES PER PERSON) OF CHILE



Source: Global Footprint Network (2022).

Colombia (figure 4), like Argentina and Brazil, still have an ecological reserve as they do not present an ecological deficit, with the gap tending to decrease.

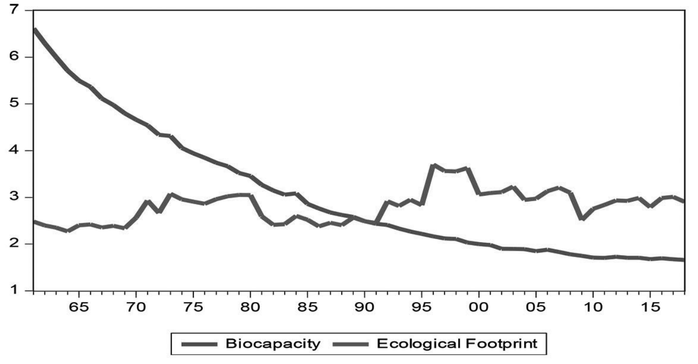
FIGURE 4
ECOLOGICAL INDICATORS (MEASURED BY GLOBAL HECTARES PER PERSON) OF COLOMBIA



Source: Global Footprint Network (2022).

Costa Rica (figure 5) shows a growing ecological deficit since the early 1990s.

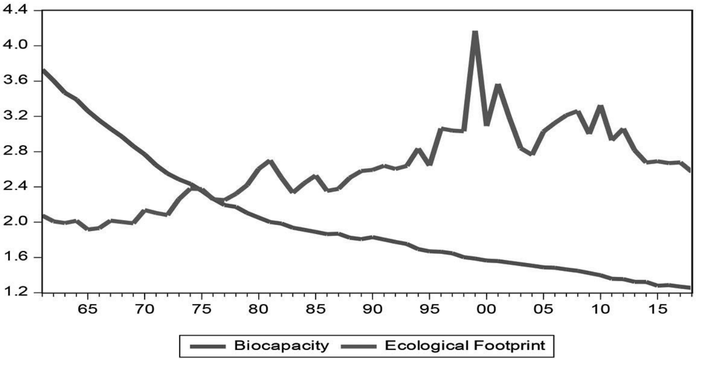
Figure 5
Ecological Indicators (measured by global hectares per person) of Costa Rica



Source: Global Footprint Network (2022).

Also, as in the case of Costa Rica, Mexico (figure 6) shows a growing ecological deficit since the 1970s.

Figure 6
Ecological Indicators (measured by global hectares per person) of Mexico



Source: Global Footprint Network (2022).

Table 2 shows three cross-sectional dependence test results, namely Breusch-Pagan LM, Bias-corrected scaled LM, and Pesaran CD. The null hypothesis is rejected in the three tests for all the variables with a significance level of 1%. Therefore, it is concluded that cross-section dependence is present in all the variables. The first and second-generation unit root tests will be used to find more robust results.

Table 2
Results of cross-sectional dependence tests

Variable	EcolF	EnerR	Gini	GDP	Patents
Breusch-Pagan LM	46.514***	70.733***	264.248***	350.455***	170.709***
Bias-corrected scaled LM	5.642***	10.064***	45.395***	61.134***	28.317***
Pesaran CD	3.029***	2.488***	6.597***	18.689***	12.488***

Note: *** and ** denote a rejection of the null hypothesis at 1% and 5% in levels, respectively.

The second-generation PESCADF test from Pesaran (2007) is applied, allowing cross-sectional dependence in the variables. Table 3 shows the results of the four tests. All the variables have unit roots in levels, and thus, there is a stochastic trend in these variables. However, they are stationary in the first differences, and thus, they reject the null hypothesis at 5% of significance or better. Therefore, the variables are integrated of order one.

Table 3
Results of unit root tests with panel data

Variable	Deterministic parameters	IPS	ADF-FISHER	PP-FISHER	PESCADF
EcolF	CT	-0.614	12.618	29.323***	0.351
EnerR	CT	0.414	9.447	12.336	1.340
Gini	CT	-1.210	21.016*	7.716	0.937
GDP	CT	-0.011	10.662	8.563	0.524
Patents	CT	-0.748	14.171	15.094	-0.710
Primera diferencia					
ΔEcolF	C	-7.934***	77.849***	145.870***	-5.876***
ΔEnerR	C	-7.168***	70.114***	106.097***	-3.467***
ΔGini	C	-1.997**	20.573**	19.194**	-5.067***
ΔGDP	C	-6.376***	60.479***	70.734***	-1.756**
ΔPatents	C	-10.167***	101.399***	116.752***+	-2.286**

Note: *** and ** reject the null hypothesis at 1% and 5% levels, respectively.

In this way, a cointegration test is necessary to test for a long-term relationship between integrated variables of the same order. The cointegration tests used in this research are: Westerlud (2007), Pedroni (1999), and

Kao (1999). The Westerlund test is adequate when the variables show cross-sectional dependence.

TABLE 4

PEDRONI TEST RESULTS

Test	Constant Statistic	Prob.	Constant and trend Statistic	Prob.
Panel v	-0.328	0.628	-0.758	0.775
Panel rho	-0.733	0.231	-0.254	0.399
Panel PP	-3.353***	0.000	-5.469***	0.000
Panel ADF	-2.841***	0.000	-4.859***	0.000
Group rho	0.290	0.614	0.975	0.836
Group P	-4.127***	0.000	-5.619***	0.000
Group ADF	-2.758***	0.000	-4.513***	0.000

Note: *** reject the null hypothesis at 1% levels.

Table 4 presents Pedroni test results, including a constant and trend, and a constant alone. In the two cases, the null hypothesis of no cointegration is rejected by the PP Panel, ADF Panel, PP Group, and ADF Group statistics at the 1% significance level. Similarly, the Kao test results are presented in table 5. The null hypothesis is rejected at the 1% significance level.

TABLE 5

KAO TEST RESULTS

t-Statistic	Prob.
-5.049 ***	0.000

Note: *** reject the null hypothesis at 1% levels.

The Westerlund (2007) cointegration test is applied since it relaxes the assumption of cross-sectional independence. Table 6 shows these results rejecting the null hypothesis of no cointegration at the 5% of significance level.

TABLE 6

WESTERLUND COINTEGRATION TEST

Statistic	P-value
-1.923**	0.027

Note: ** reject the null hypothesis at 5% levels.

Therefore, based on the three cointegration tests, a long-term equilibrium relationship between variables is tested, which implies that the regression model is not spurious and that the statistical inference is reliable.

However, in this case, the OLS estimation coefficients could be biased and inconsistent. Nevertheless, the FMOLS estimator generates consistent estimates, allowing for controlling the endogeneity of regressors and serial correlation (Pedroni, 2001).

Table 7
Long-term coefficients results

Variable	FMOLS Coefficients	PCSE Coefficients
EnerR	-0.062*	-0.019
Gini	0.102***	0.680**
GDP	0.122***	0.491***
Patents	-0.053**	-0.001

Note: ***, **, and * reject the null hypothesis at 1%, 5%, and 10% levels, respectively.

The results in table 7 show FMOLS and PCSE estimators regarding the long-term elasticities. The coefficient is negative and statistically significant in the case of Patents with the FMOLS but not with the PCSE estimator. Allard *et al.* (2018), Chen *et al*. (2019), and Gómez and Rodríguez (2020) did not find statistically significant coefficients as well. The same happens with EnerR; the coefficient is negative and statistically significant with the FMOLS. Results with a negative and statistically significant relationship between renewable energy and environmental degradation are also found in Wolde-Rafael and Mulat-Weldemeskel (2022) for 18 countries in Latin America and the Caribbean and Gómez and Rodriguez (2020) for the UMSCA countries. Regarding economic activity, the relationship is positive and statistically significant for the three estimators at 5% or better, implying that as economic activity increases, energy consumption increases too, and thus it causes greater environmental degradation.

Considering the Gini coefficient, the two estimators confirm a positive and statistically significant relationship at 5% significance or better. This fact implies greater environmental degradation if there is more inequality. Latin America has been characterized as one of the regions with the greatest inequality; it is to be expected that when most people barely satisfy their basic needs, they will not worry about environmental degradation. The richest countries tend to have relatively cleaner urban air and cleaner river basins because they have stricter environmental standards and environmental rights enforcement than low and middle-income countries (Noce, 2011). Countries with high inequality tend to get less support for environmental protection (Ridzuan, 2019) because they are more concerned with daily survival and less interested in pursuing environmental policies (Stiglitz, 2014).

The moments quantile regression method allows testing for robustness in the model (table 8).

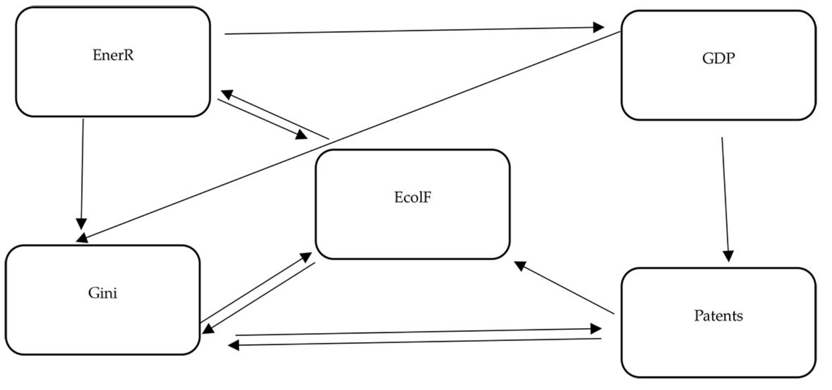
Table 8
Panel Quantile Estimation Results

Variables	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
EnerR	-0.208*	-0.180**	-0.156**	-0.127*	-0.107	-0.075	-0.043	-0.006	0.040
Gini	0.488**	0.399*	0.323*	0.229	0.165	0.063	-0.036	-0.154	-0.303
GDP	0.187**	0.178**	0.169***	0.159***	0.152***	0.140**	0.129*	0.116	0.100
Patents	-0.053*	-0.051**	-0.050**	-0.049***	-0.048***	-0.046**	-0.044**	-0.042	-0.040

Note: ***, **, and * reject the null hypothesis at 1%, 5%, and 10% levels, respectively.

Almost all quantile regression results are the same as in the FMOLS estimation. In the first three quantiles, the coefficients of the four variables have the expected signs. They are statistically significant, and thus, in the distribution's lower part are the explanatory variables' expected effects. The previous implies that renewable energies and the technological development generated through patents reduce environmental degradation. Meanwhile, greater income inequality and greater economic activity generate greater environmental pollution. In the case of the coefficients of economic activity and patents, they are statistically significant and with the expected signs of quantile 1 to 7. A long-term relationship between variables implies a causal relationship in at least one direction (Granger, 1988). Thus, the causality test in heterogeneous panel data models must be applied is applied.

FIGURE 7
HETEROGENEOUS CAUSALITY TEST RESULTS



Source: From the results of the causality test presented in Table 9.

There is some theoretical and empirical literature that indicates that there is a relationship between innovation (it could be measured through the number of patents) and income inequality. In most empirical results, the relationship is positive; that is, greater innovative activity can increase income inequality by increasing the return on assets (for more details, see Chu, 2010; Guillén Maqueda and Godínez Enciso, 2022; Hu *et al.,* 2023). There is a bidirectional causality relationship between Gini and EcolF, EnerR and EcolF, Patentes, and Gini, indicating that the variables are complementary (figure 7 and table 9). Each has important information that helps better predict the behavior of the other. In addition, there is a unidirectional causality relationship from Patents to EcolF, implying that a patenting activity change affects EcolF. These causality results confirm the importance and predictive power of patenting activity, renewable energy, and income inequality on environmental degradation measured by the ecological footprint in the selected Latin American countries. Also, a unidirectional causality relationship from GDP to Gini and Patents exists, implying that economic activity contains essential information that better predicts the behavior of income inequality and patenting activity. In this same sense, there is also a unidirectional causality relationship from EnerR to Gini and GDP, implying that economic activity contains essential information that helps predict the behavior of income inequality and economic activity.

Table 9

Results of the heterogeneous causality test

Null hypothesis	Zbar-Stat.	Decision
Gini does not homogeneously cause EcolF	3.694***	Reject
EcolF does not homogeneously cause Gini	1.657*	Reject
GDP does not homogeneously cause EcolF	0.396	Accept
EcolF does not homogeneously cause GDP	1.125	Accept
Patents do not homogeneously cause EcolF	1.760*	Reject
EcolF does not homogeneously cause Patents	0.242	Accept
EnerR does not homogeneously cause EcolF	2.568**	Reject
EcolF does not homogeneously cause EnerR	1.952**	Reject
GDP does not homogeneously cause Gini	4.890***	Reject
Gini does not homogeneously cause GDP	1.620	Accept
Patents do not homogeneously cause Gini	3.410***	Reject
Gini does not homogeneously cause Patents	2.310*	Reject
EnerR does not homogeneously cause Gini	2.571**	Reject
Gini does not homogeneously cause EnerR	1.271	Accept
Patents do not homogeneously cause GDP	1.580	Accept
GDP does not homogeneously cause Patents	2.624***	Reject
EnerR does not homogeneously cause GDP	3.138***	Reject
GDP does not homogeneously cause EnerR	0.583	Accept
EnerR does not homogeneously cause Patents	0.163	Accept
Patents do not homogeneously cause EnerR	1.005	Accept

Note: *** and ** denote statistical significance at the 1 and 5 percent levels, respectively.

3. Discussion

According to Moreno (2020), the Latin American region is one of the regions with the highest inequality in terms of labor income. Nevertheless, Messina and Silva (2017) suggest that during the 1990s and 2000s, certain trends favored labor income equality in the region by improving some factors related to labor supply (e.g., expansion of education and the fall in its returns), conditions related to labor demand (e.g., technological change and trade liberalization), and institutional factors (e.g., formalization of employment). However, these trends are not observed in the long term, and Latin America may continue as one of the regions with the most significant inequality in labor income globally. In general, Chile, Costa Rica, and Mexico exceeded the ecological footprint over their biocapacity, which means an ecological deficit. In the same way, Argentina, Brazil, and Colombia still have an ecological surplus with a clear trend to reduce it.

Concerning Patents, the coefficient is negative and statistically significant. Technological development, measured through granted patents, contributes to reducing environmental degradation. In other similar studies, Allard *et al.* (2018), Chen *et al.* (2019), and Gómez and Rodríguez (2020), no statistical evidence was found of the relationship between these variables. In the same way, the coefficient of EnerR is negative and statistically significant. These results are similar to those found by Wolde-Rafael and Mulat-Weldemeskel (2022) for 18 countries in Latin America and the Caribbean and by Gómez and Rodríguez (2020) for the UMSCA countries. Regarding economic activity, the relationship is positive and statistically significant, which implies that as economic activity increases, energy consumption also increases, causing greater environmental degradation.

Considering the Gini coefficient, it confirms a positive and statistically significant relationship. This implies that as there is more inequality, there is more environmental degradation. Latin America has been characterized as one of the regions with the greatest inequality; it is to be expected that when most people barely satisfy their basic needs, they will not worry about environmental degradation. The richest countries tend to have cleaner urban air and river basins as they have stricter environmental standards and enforcement of environmental rights concerning low and middle-income countries (Noce, 2011). Future research could use non-linear econometric methods and add variables, such as poverty, etc., that can influence environmental degradation.

Conclusions

This research examines the impact of income inequality and patenting activity on environmental degradation in six selected Latin American countries (1991-2018). The results suggest that variables are characterized by transversal dependence and integrated of order one. There is a long-run equilibrium relationship between variables. Furthermore, long-term modeling results show that renewable energy and patenting activity reduce environmental degradation, while income inequality and economic growth increase it. Therefore, it is essential to promote renewable energies, patenting activity of cleaner technologies, and environmental regulation to reduce environmental degradation. Finally, it is urgent to design and apply income redistribution policies to reduce environmental pressure.

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