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INCOME INEQUALITY AND CARBON DIOXIDE EMISSIONS: EVIDENCE FROM LATIN AMERICA

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ABSTRACT: The recent literature has explored the ambiguous theoretical links between inequality and environmental impact. However, few studies have investigated those links in developing countries. This paper explores the role of income inequality in the per capita emission of CO_2 in Latin America. We estimate the impact of income inequality on carbon dioxide emissions, while simultaneously considering national income levels. The results suggest quadratic relationships between environmental impact and both gross domestic product per capita and inequality. Income inequality influences CO_2 emissions, but the direction depends on income level. The complexities of the results are analytically explored in the paper. © 2020 John Wiley & Sons, Ltd.

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1 INTRODUCTION

The notion that human activities generate environmental impacts is quite intuitive. In any society which exploits natural resources, even minimally, each individual will have an impact on the environment because of the destabilization of natural ecosystems (Ehrlich & Holdren, 1971; Jackson, 2009). However, establishing the relationship between economic activity and environmental impact in a systematic way that would be of use in the planning and evaluation of sustainable development remains a constant challenge for scholars.

Considering economic dynamics, there is evidence that, at least up to a certain level of income, growth is accompanied by an increase in environmental impact (Grossman & Krueger, 1995). On the other hand, when accompanied by a reduction in inequality, growth is considered an important factor for the reduction of poverty (Dollar & Kraay,

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2002; Kakwani & Pernia, 2000). Therefore, achieving a balance between growth, reduced inequality and environmental sustainability is one of the greatest challenges facing society, which is corroborated by the fact that these dimensions, although independently, are among the United Nations 17 Objectives for Sustainable Development, adopted in early 2016 (UN, 2017).

The last four decades of the 20th century saw the publication of numerous studies that sought a more objective relationship between population, economic activity and environmental pressure (Dietz & Rosa, 1994; Ehrlich & Holdren, 1972; Grossman & Krueger, 1991; Pearce, Hamilton & Atkinson, 1996). But it was only in the mid-1990s that the issue of inequality appears clearly in the literature. Initially, the most prominent studies were those of Boyce (1994), who advocates a direct relationship between inequality and environmental degradation and Scruggs (1998), who suggests the opposite.

Berthe and Elie (2015) offer an extensive review of the evolution of this debate, presenting both the arguments and the empirical results of a systematically revised set of studies. According to the authors, there is no consensus regarding the ways in which income inequality and environmental impact interact, and one third of the studies find no such relationship exists.

While the variable of choice for measuring inequality has been the Gini index, studies in the literature have used a range variables related to environmental impact, including carbon dioxide (CO_2) emission, water, air or soil pollution and, to a lesser extent, composite variables of environmental pressure, such as the ecological footprint (Clément & Meunié, 2010; Heerink, Mulatu & Bulte, 2001; Torras & Boyce, 1998).

In relation to geographical area, the vast majority of studies focus on developed regions of the world or on panels that simultaneously consider several regions. The study by Clément and Meunié (2010) can be considered an exception, because it studies countries of Central and Eastern Europe.

Among the more recent literature, three papers stand out that will be the starting point for the contributions of this article. Dorsch and Kirkpatrick (2014), Grunewald, Klasen, Martínez-Zarzoso and Muris (2017) and Knight, Schor and Jorgenson (2017) empirically evaluate the existence of the relationship between inequality and environmental impact. Each one with peculiarities regarding the group of the countries considered, the econometric specifications and the variables that denote inequality and environmental impact, but all offer contributions that are at the leading edge of research in the area.

Considering the lack of studies specifically dedicated to developing regions as well as the constant evolution in terms of econometric implementation, this paper aims to evaluate the impact of income inequality on CO_2 emissions in Latin America. The present study focuses on, in addition to the unprecedented regional application, an econometric specification that deals with the impact of income inequality on CO_2 emissions, while simultaneously taking into account the income levels in the countries, which refers to the hypothesis of the environmental Kuznets curve (EKC). To deal with endogeneity and other issues associated with this sort of empirical application, a dynamic data panel model is applied, as suggested by Arellano and Bond (1991).

2 THEORETICAL AND EMPIRICAL REFERENCE

The classic studies by Ehrlich and Holdren (1971, 1972) and Commoner (1972) suggest the environmental impact is a product of population, affluence and technology. Known

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as the IPAT[1] model, this is the first empirical systematization of the relationship between anthropic pressure via economic activity and environmental impact. In the 1990s, to that basic accounting model, Dietz and Rosa (1994) add a stochastic approach towards the relationship between the those variables, resulting in the STIRPAT[2] models. This type of model allows the addition of other variables, so that evidence was found to show the level of industrialization (York, Rosa & Dietz, 2003), urbanization (Fan, Liu, Wu & Wei, 2006; Liddle & Lung, 2010; Mattos & Filippi, 2014; York et al., 2003) and age structure (Liddle & Lung, 2010) are important environmental impact factors.

In this context, several particular arguments about the relationship between economic dynamics and environmental pressure have also emerged. Perhaps the best known is the EKC hypothesis, which suggests environmental degradation increases in the early stages of development and decreases in the more advanced stages, establishing an inverted U-shape for this relationship (Grossman & Krueger, 1991).

Within the extensive literature on EKC, there is little consensus regarding the validity of the hypothesis. The study by Dinda (2004) compiles a large set of papers, indicating the main explanations for the shape of the curve. The arguments range from structural change in the economy, which would shift from an agricultural base towards industrialization and technological change, to microeconomic explanations dealing with the change in the marginal propensity to consume. Thus, although econometric issues are controversial (Stern, 2004), the proposal has enormously stimulated debate on the subject.

In the same wave of research that began in the 1990s, scholars began to consider inequality as an important factor to explain environmental pressure. The paper by Torras and Boyce (1998) is of particular interest here. In addition to testing the EKC hypotheses, this is one of the first empirical studies to use income inequality as an inducer of environmental impact. They used the theory developed in Boyce (1994), which postulates that the balance between consumption and environmental quality would occur through what he called the power-weighted social decision rule (PWSDR).

In this theoretical model, economic activities that degrade the environment generate advantages for some (winners) and disadvantages for others (losers). The winners are producers who do not have to bear the costs of production-generated pollution, as well as consumers who access those products at lower prices. The losers are those affected by the pollution generated by that production or consumption. Social balance, in a cost–benefit analysis context, before considering inequality, would occur at the level of pollution that maximizes the aggregate net benefit.

Then, what determines whether the PWSDR will result in greater environmental devastation is the correlation between power and benefit. For Torras and Boyce (1998), there are reasons to expect that a greater net benefit is associated with higher individual income and to power. The idea is that, producing goods without considering the environmental degradation in their prices and costs generates a surplus for the consumer and the producer. Individuals with higher incomes, because they have more assets and consume more, also access most of the surplus. Therefore, there would be a correlation between benefit and individual income. Power, in turn, would also be correlated with income. Thus, higher levels of income inequality would be associated with a balance of power favourable to the environmental impact, which was empirically confirmed in Torras and Boyce (1998).

[1]IPAT means impact, population, affluence and technology.
[2]STIRPAT means STochastic Impacts by Regression on Population, Affluence and Technology.

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The studies by Borghesi (2006) and Marsiliane and Renstrom (2003) also lend strength to the argument that greater inequality tends to generate greater environmental degradation. Those papers, however, point to a more political channel, where decisions on environmental protection are influenced by the imbalance of power in the conduct of environmental policy.

Scruggs (1998) points to an inverse relationship, making two important critiques of Boyce's theoretical model (Boyce, 1994). First, assuming a positive correlation between income and environmental impact implies the marginal demand for environmental impact increases in line with income. This, according to the author, contradicts theoretical and empirical evidence that suggests members of society with high incomes tend to be more concerned about the environment than those with low incomes. Second, democratic environments where there is greater equality of power can lead to divergent environmental outcomes, while non-democratic institutions with acute inequality of power can produce beneficial environmental outcomes. In his empirical tests, he found no evidence that economic equality and democracy help explain variations in environmental quality.

In addition to Scruggs (1998), Ravallion, Heil and Jalan (2000) and Heerink et al. (2001) argued that, as the marginal propensity to consume would decrease as income increased, the marginal propensity for degradation would also decrease: The rich would allocate a diminishing proportion of their income to consumption, marginally reducing pollution. Thus, growth with inequality, privileging the more affluent, would have less environmental impact than growth with equality.

The hypotheses offered by Boyce (1994) and rejected by Scruggs (1998) are central to the most recent studies on the subject. Dorsch and Kirkpatrick (2014), using the ecological footprint as a measure of environmental quality in a fixed-effects panel, sought evidence that the EKC would only be significant when the model is controlled by the level of income inequality, measured by the Gini coefficient. Despite being unable to confirm the EKC, their results showed that growth with equality is less damaging to the environment, which is in line with Boyce (1994).

Grunewald et al. (2017) provide a methodological innovation in using a fixed-effect panel by group of countries, which would better deal with the heterogeneity not observed over time. The authors conclude that, for the group of lower income countries, a reduction in inequality would have a negative effect on the environment, which supports the idea of marginal propensity for downward degradation suggested by Scruggs (1998). However, for the group of high income countries, the reduction of inequality would reduce the impact, which supports the PWSDR proposed by Boyce (1994). Similarly, Jorgenson, Schor, Knight and Huang (2016), when clustering countries by high, medium and low income, showed that carbon emissions and income inequality are positively associated in rich countries and negatively associated in middle-income countries.

Considering high income countries alone, Knight et al. (2017) found evidence of PWSDR in CO_2 emissions. The author tests a new variable as a measure of inequality, namely, the concentration of wealth measured based on the percentage held by the first decile. According to them, the level of wealth is more associated with power, and thus is better for testing Boyce's model (1994), because income inequality would have a greater effect on consumption patterns and none on the distribution of power.

In short, just as the classical literature on the subject contains theoretical arguments that support both a direct and inverse relationship between inequality and environmental impact, the empirical evidence is similarly ambiguous. The present study seeks to

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Table 1. Number of observations and countries in the sample

Country	Number of observations	Coverage
Argentina	44	100%
Bolivia	24	55%
Brazil	44	100%
Chile	44	100%
Columbia	44	100%
Costa Rica	44	100%
El Salvador	23	52%
Ecuador	27	61%
Guatemala	33	75%
Honduras	26	59%
Mexico	44	100%
Panama	44	100%
Paraguay	24	55%
Peru	42	95%
Uruguay	33	75%
Venezuela	44	100%
Total	584	83%

Source: elaborated by the authors.

contribute to this area by proposing a study applied to Latin American countries following the most recent papers, while suggesting a dynamic panel data model.

3 SAMPLE AND DATA

Considering the particular interest in the developing countries, our area of study will be Latin America, a region with considerable cultural homogeneity that has been rarely explored in this type of analysis. The United Nations Statistical Division standard was used—through the online publication Standard Country or Area Codes for Statistical Use (UN, 2017), considering countries under the definition of Latin America and the Caribbean.

The time period established is 44 years, from 1970 to 2013, based on the period covered by the data. Considering the absence of data from some countries for several years, and in order to favour a more balanced panel, those with less than 50% of the analysed period were removed from the sample.[3] Given that only three Caribbean countries met this criterion[4]—all classified as Small Island Developing States (NATIONS, 2017)—in order to ensure a homogeneous base, those three countries were also removed from the sample. Thus, this study is restricted to Latin America, with 16 countries studied, totalling 584 observations. Table 1 shows the distribution of observations by country.

As in the main studies on this subject, the Gini coefficient will be used to measure income inequality. Data from Solt (2017) will be used, which provide the Standardized World Income Inequality Database. This database brings together several data sources that

[3]Thirteen countries were removed from the sample because of this criterion: Antigua and Barbuda, Bahamas, Belize, Dominica, Grenada, Guyana, Haiti, Jamaica, Nicaragua, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines and Suriname.
[4]Namely, Barbados, Dominican Republic and Trinidad and Tobago.

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Table 2. Descriptive statistics

Variable	Source	Unit	Mean	SD	Min	Max
CO_2 per capita	ORNL/WDI	T	1.94	1.47	0.25	7.61
GDP per capita	PWT	US$ 2011	8 824	4 168	2 708	21 197
Gini[1]	SWIID		47.09	4.44	34.79	55.22

Source: elaborated by the authors.
[1]In the case of the Solt data (2017), the Gini index varies from 0 (perfect equality) to 100 (perfect inequality).

maximize the comparability between the years and countries. The information has been updated since its first publication, in Solt (2009), with revisions of methodology and new data. This database is also used in the main reference articles of this study, such as Dorsch and Kirkpatrick (2014), Knight et al. (2017) and Grunewald et al. (2017).

As the measure of gross domestic product (GDP), data for real GDP in 2011 dollars, taken from version 9.0 of the Penn World Tables (Feenstra Robert & Timmer, 2015) were used. This database is the same as that used by Dorsch and Kirkpatrick (2014). For data on CO_2 emissions, data from the Oak Ridge National Laboratory data (Boden, 2017), a United States government agency, made available by the World Bank through the World Development Indicators were used. The data are CO_2 emissions from fossil fuel combustion (solid, liquid and gaseous) and cement manufacture, compatible with those used in the literature. To obtain the per capita information, the population data available in the Penn World Tables were used.

The descriptive statistics of the variables used can be found in Table 2. In it, one can see there is a wide range of values for CO_2 per capita, with the highest value being almost 30 times that of the lowest. It is important to note that Venezuela dominates the highest per capita emission values, especially because of the high energy consumption (Robalino-López, Mena-Nieto, Garica-Ramos & Golpe, 2015), with practically all the values surpassing those of the other countries. Then we have Chile, Argentina and Mexico with the highest values, especially in recent years. The countries with the lowest emissions are Paraguay, El Salvador and Guatemala.

The values for GDP per capita are also wide ranging, although the variability is practically half that observed in the case of CO_2 emissions. The highest values are from Argentina and Chile in recent years and some values from Venezuela between 1976 and 1979.[5] The lowest figures are found in Honduras, Bolivia and Paraguay, especially for values prior to the 1990s.

The measures of inequality are less dispersed. Nonetheless, countries such as Argentina, Venezuela and Uruguay dominate the lowest values, with a less unequal income distribution, with the nine lowest values being Argentina in the 1970s. At the other extreme, Bolivia has the three highest indexes (for the years 2000–2002). Peru is consistently among the most unequal, with 15 of the 20 highest records. In recent years, as of 2009, Colombia, Honduras and Chile are the countries with the highest levels of inequality, while Uruguay, Venezuela and Argentina remain the most equal countries.

[5]Venezuela's economy is highly dependent on international oil prices, and this influences the fluctuations in per capita (Robalino-López et al., 2015).

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4 ECONOMETRIC MODELS

The core approach adopted in this study is inspired by the most recent literature on the topic. The study by Dorsch and Kirkpatrick (2014) employed a fixed-effects model, allowing a nonlinear relationship of income with environmental pressure measured by the ecological footprint, to test for the EKC, and permitted the inequality variable to interact with GDP per capita and GDP per capita squared. The objective of their study was to point out that the EKC was only observed at certain levels of inequality.

The study by Grunewald et al. (2017), on the other hand, tested the impact of inequality at different levels of GDP per capita on CO_2 emissions. To do so, they used a fixed effects model by country together with grouped fixed effects. The authors did not contemplate the idea of non-linearity in the relation between inequality and GDP per capita, because the specification did not include the interaction between Gini and GDP per capita squared.

Knight et al. (2017) used data on wealth inequality and income inequality simultaneously, in addition to the interaction of wealth inequality by year, in order to investigate the evolution of elasticity over time for high income countries. However, they did not consider the interaction of the main independent variables with the GDP, thus it is impossible to test if elasticity changes at different average levels of per capita income.

Based on the ideas contained in those papers, the present study focuses on assessing of the impact of income inequality on per capita CO_2 emissions at different levels of GDP per capita while also checking for the presence of the EKC. Moreover, in addition to the special focus on the Latin American countries, the method proposed here also differs from those earlier papers with regards the category of the econometric model adopted.

The studies by Dorsch and Kirkpatrick (2014) and Knight et al. (2017) both proposed models in reduced form, which consequently lack control variables. Such models are prone to suffer from endogeneity between the environmental and income variables, which is not properly addressed by ordinary least squares estimators (Parajuli, Joshi & Maraseni, 2019).

Grunewald et al. (2017), in turn, included some controls (referred to as transmission channels) and applied grouped fixed effects. However, the absence of endogeneity is not guaranteed, because it is quite difficult to test for. One way to address this issue is through the instrumental variables approach, as proposed by Lin and Liscow (2013) and Lorente and Álvarez-Herranz (2016). In this case, though, the persisting challenge is to find suitable instruments for the model.

Taking those arguments into consideration, this study proposes to estimate the reduced models via generalized methods of moments (GMM), as proposed by Arellano and Bond (1991)[6]—similar approach can be found in Beck and Joshi (2015) and Parajuli et al. (2019). The Arellano–Bond approach is a dynamic data panel model which uses lagged variables as instruments. In doing so, both the endogeneity and the country-specific heterogeneity are addressed. And it is worth mentioning that this model can also capture the persistent effect of environmental pressure over the upcoming periods.

[6]We have also tested the System GMM approach as proposed by Blundell and Bond (1998). However, because our sample has a relatively high number of years and the AR component of the estimated model was not close to one, there was no reason to choose system GMM over the difference GMM.

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In this paper, we employ Arellano–Bond's approach to estimate a series of models with varying levels of complexity. All the variables are in logarithmic form. Considering c_{it} the per capita CO_2 emissions, $c_{i(t-1)}$ the first lag of the per capita CO_2 emissions and y_{it} the GDP per capita; α and γ, respectively, the fixed effects of the cross-sectional unit (country) and time unit (year); μ the term of residuals; i the subscript denoting the cut-off unit and t time; the first model is presented in Equation (1).

$$c_{it} = \alpha_i + \gamma_t + \beta_1 c_{i(t-1)} + \beta_2 y_{it} + \beta_3\, y_{it}^2 + \mu_{it} \tag{1}$$

Note that the EKC can be found when $\beta_2 > 0$ and $\beta_3 < 0$. This is the classic EKC model, which does not consider the impact of inequality.

Now, considering g_{it} the income inequality measured by the Gini coefficient and g_{it}^2 its square, we will obtain the first results for the impact of income inequality on per capita CO_2 emissions through the models in Equations (2) and (3).

$$c_{it} = \alpha_i + \gamma_t + \beta_1 c_{i(t-1)} + \beta_2 y_{it} + \beta_3\, y_{it}^2 + \beta_4 g_{it} + \mu_{it} \tag{2}$$

$$c_{it} = \alpha_i + \gamma_t + \beta_1 c_{i(t-1)} + \beta_2 y_{it} + \beta_3\, y_{it}^2 + \beta_4 g_{it} + \beta_5\, g_{it}^2 + \mu_{it} \tag{3}$$

In these simplified models, the effect of the inequality will be given by the sign of the coefficient β_4 in model (2) and by the sign of coefficients β_4 and β_5 in model (3). For the model (2), the coefficient is positive in the case of greater inequality increasing emissions and negative in the case of greater inequality decreasing emissions. The model (3) brings more complexity to the analysis because it allows for a non-linear relationship between inequality and per capita CO_2 emissions—the shape of the relationship will be determined by the combinations of the signs of the coefficients β_4 and β_5.

Models (2) and (3) do not allow us to properly test for a change in the direction of the impact as the level of the GDP per capita varies, as seen in Dorsch and Kirkpatrick (2014) and Grunewald et al. (2017). For this purpose, the interactions between Gini and GDP per capita should enter the model, as presented in Equation (4).

$$c_{it} = \alpha_i + \gamma_t + \beta_1 c_{i(t-1)} + \beta_2 y_{it} + \beta_3\, y_{it}^2 + \beta_4 g_{it} + \beta_5\, g_{it}^2 + \beta_6\, y_{it} g_{it} + \mu_{it} \tag{4}$$

In this more complex model, we can still test for the existence of the EKC, but it will be conditioned by the level of inequality, as in Dorsch and Kirkpatrick (2014). As we work with all the data in logarithmic form, the coefficients represent the elasticities. And this study is especially interested in the elasticity of per capita CO_2 emissions in relation to both income inequality (εg_{it}) and GDP *per capita* (εy_{it})—as derived bellow.

$$\varepsilon g_{it} = \frac{\partial c_{it}}{\partial g_{it}} = \beta_4 + 2\beta_5 g_{it} + \beta_6 y_{it} \tag{5}$$

$$\varepsilon y_{it} = \frac{\partial c_{it}}{\partial y_{it}} = \beta_2 + 2\beta_3 y_{it} + \beta_6 g_{it} \tag{6}$$

The signs of the $\beta\,'\,s$ will determine the shape of the curves. For example, for εg_{it}, if all the $\beta\,'\,s$ have the same sign, it means that the effect points in the same direction for any level of GDP per capita—if all the coefficients were positive, it would indicate that in all cases an increase in inequality causes a rise in CO_2 emissions. A more complex case, with alternating signs, would show the elasticity can change direction according to the size of the average income and the Gini level.

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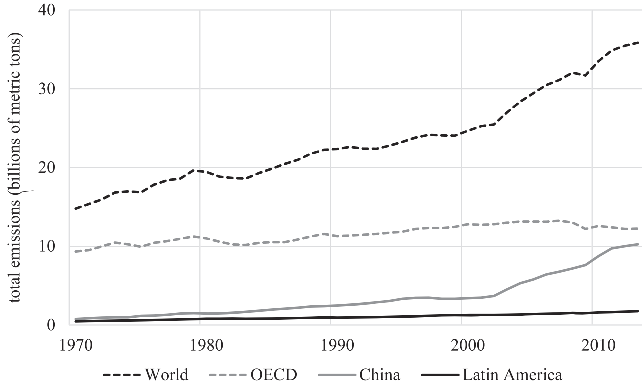

Figure 1. Total CO_2 emissions in regions of interest Source: ORNL/WDI

5 RESULTS AND DISCUSSION

In a preliminary analysis of the data, with some regional groupings[7] plotted in Figure 1, CO_2 emissions can be seen to have grown consistently since the beginning of the studied period. According to Peters et al. (2012), there is a reduction in CO_2 emissions per dollar of GDP, demonstrating efficiency gains in production. Nevertheless, this insufficient to avoid the increase in emissions because of population growth and economic activity—a phenomenon discussed in UNEP (2011) that deals with relative and absolute decoupling between economic growth and environmental impact. Since the 2000s, the gains in production efficiency have slowed down, which, coupled with continued economic growth, has resulted in a steeper rise in emissions (Raupach et al., 2007).

The figure shows that the Latin American countries account for only a small proportion of world emissions. However, like other developing countries, their participation has been growing. While world emissions have increased an average of 2.0% per year (p.y.) and in Organisation for Economic Cooperation and Development (OECD) member countries they grew by 0.6% p.y., in Latin America and China growth rates were 3.0% p.y. and 6.0% p.y., respectively. Raupach et al. (2007), in their analysis of the main drivers of emissions growth from the 1980s to 2007, showed production in China has become less carbon intensive because of various improvements in energy efficiency, but the accelerated growth of GDP per capita means it is the region with the highest increase in emissions. According to the authors, in other developing countries, there has been no significant improvement in energy efficiency, and growth can be explained by expanding population and GDP per capita.

Considering the average emissions, outlined in Figure 2, the OECD member countries can be seen to still produce, in proportion to population, the highest emissions. However, over the period the difference has diminished, especially in relation to China, which, from the decade of 2000, saw very accelerated per capita income growth. In Latin America, per capita emissions growth was also higher than in the world and OECD countries. According to Economic Commission for Latin America and the Caribbean (ECLAC; 2014), one reason is that energy demand in the region responds more intensely to GDP growth,

[7]For regional cluster analyses, population data are those available from the WDI because the PWT does not provide clusters for the regions of interest.

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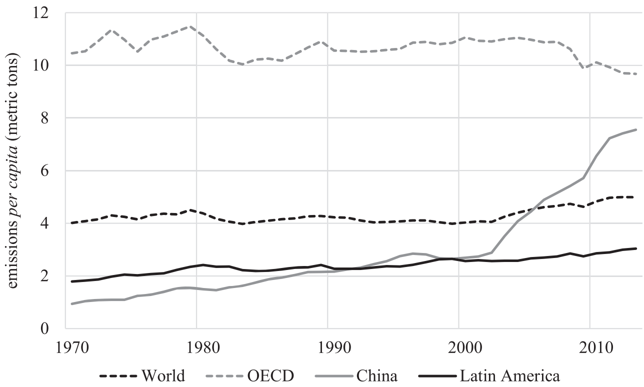

Figure 2. Per capita CO_2 emissions in the regions of interest Source: ORNL/WDI for emissions data and WDI for population data

supporting the hypothesis of stagnation in energy efficiency in developing countries, presented by Raupach et al. (2007). Moreover, according to the report, the increased income caused a change in consumption patterns, as poorer families began to access new, more carbon intensive products, which contributed to the accelerated increase in per capita emissions.

The consumption pattern within a society is also related to its social structure, in which income inequality plays an important role. Figure 3 shows the evolution of the Gini coefficient in the sampled countries. There is an evident reduction in inequality for almost all the countries, especially from 2000. There are two main reasons for this trend. First, there was an increase in and a better distribution of government transfers, which reduced non-labour income inequality (Lustig, Lopez-Calva, Ortiz-Juárez & Monga, 2016; OECD, 2015). Second, there was a reduction in the education premium during the period (salary return expected per year of study), which reduced wage differences.[8]

The decline in inequality, coupled with the growth of per capita income, led to an expansion of the middle class. Azevedo, López-Calva, Lustig and Ortiz-Juárez (2015), in analysing the contribution of economic growth and inequality in the size of the middle class in the 2000s, has shown that, on average, 21% of the increase in the size of the middle class can be explained by the reduction in inequality. In addition, about 40% of the reduction in poverty is also related to better income distribution. And this social ascension modified consumption patterns.

The ECLAC (2014) report, when comparing the proportion of types of expenditure of the first and 10th income deciles, showed the more affluent families allocate a higher proportion of spending on housing, health, transport, education and financial services—products involving more intensive carbon use, especially transport—while the poorest households allocate a larger proportion to food and clothing. Additionally, according to Bárcena, Prado, Samaniego and Pérez (2014), the poor quality of public transport in the region means the increase in family income intensifies the use of private cars, with a large increase in the fleet and consequently in fuel consumption. In this sense, a reduction in inequality associated with higher income levels can change the consumption pattern and

[8]The causes of the reduction in this premium have not yet been fully determined, and may be the result of increased access to education, especially higher education, reduced demand for specialized work (Lustig et al., 2016; OECD, 2015) or a deterioration in the quality of education (Azevedo et al., 2015).

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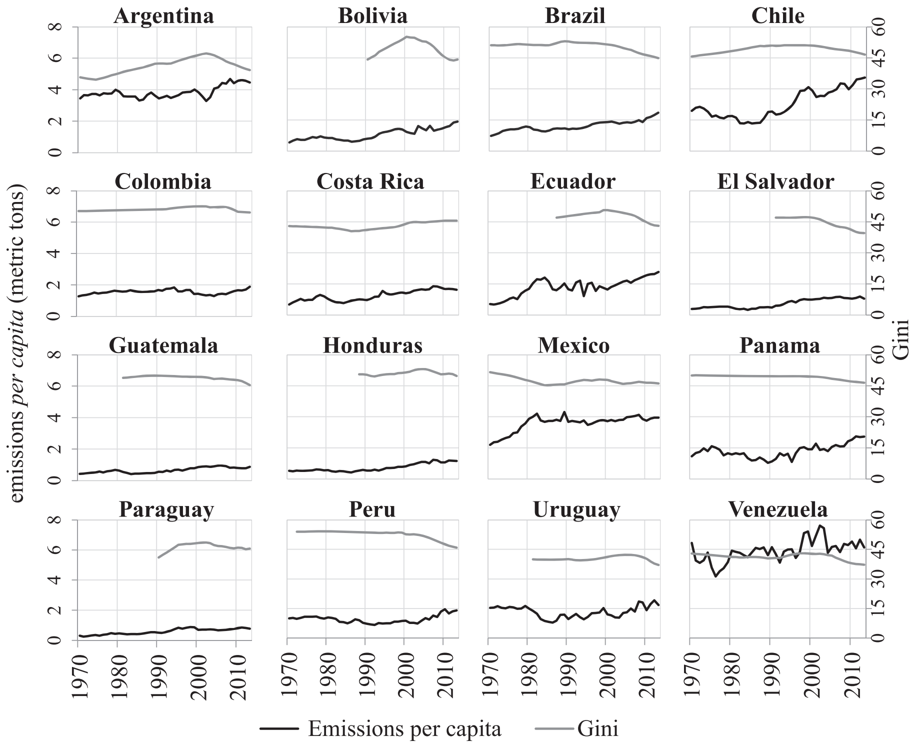

Figure 3. Emissions of CO_2 per capita and Gini coefficient for the sampled countries Source: PWT for population data, SWIID for Gini data and ORNL/WDI for emissions data

increase emissions. This lends weight to the hypothesis that the level of inequality associated with GDP per capita impacts on CO_2 emissions.

In Figure 4, we can see how per capita CO_2 emissions behave as a function of the Gini coefficient. The relationship appears to be negative, with higher levels of inequality related to lower emission levels. This relationship seems to corroborate Scruggs' (1998)

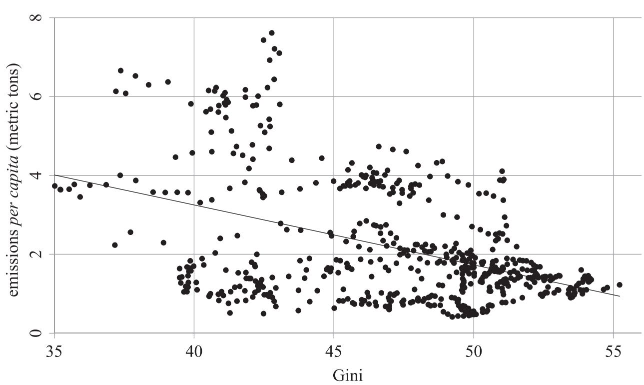

Figure 4. Scatter plot of per capita CO_2 emissions as a function of income inequality for the sampled countries in the period 1970–2013 Source: PWT for population data, SWIID for Gini data and ORNL/WDI for emissions data

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hypothesis, as refined by Ravallion et al. (2000) and Heerink et al. (2001), that the marginal propensity for degradation is decreasing in income. This implies that adding 1 dollar to the income of a poorer individual generates a greater impact on emissions than adding 1 dollar to the income of a wealthier one. Therefore, economic growth coupled with a reduction in income inequality that favours the less affluent, would have a greater impact on emissions.

These data also make sense when compared with the analysis of social mobility and growth of the middle class as a function of the reduction of inequality made by Azevedo et al. (2015) and with the evaluation of the change in consumption patterns in the region, carried out by ECLAC (2014). However, the impact of GDP per capita growth, the main driver of emissions, must be taken into account, as well as the hypothesis that the relationship between inequality and per capita emissions is conditional on per capita product, according to recent studies by Grunewald et al. (2017) and Dorsch and Kirkpatrick (2014). These hypotheses will be tested in the econometric models developed in the present study.

When we assess the behaviour of per capita emissions as a function of GDP per capita levels, Figure 5 shows a positive relation. Considering that a higher average income implies a higher consumption of carbon-intensive goods and services, this relationship has been predicted since the first discussions on the subject (Commoner, 1972; Ehrlich & Holdren, 1971). Visually, however, it is impossible to establish the inverted U-shape expected by the EKC. Recent studies have tested the existence of the curve for Latin America and the Caribbean and reported mixed results. Using energy consumption as a variable representing environmental pressure and gross value added as a control, for the period 1990 to 2011, Pablo-Romero and Jesús (2016) found no evidence of the curve in the region. Similarly, Zilio and Recalde (2011), in a broader temporal analysis (1970–2007) and also using energy consumption as an environmental variable, but with GDP as an independent variable, found no evidence of the EKC. By contrast, Al-Mulali, Tang and Ozturk (2015) used the CO_2 emissions of Latin America and the Caribbean as a dependent variable between 1980 and 2010, and their results indicated the existence of the EKC.

Therefore, there is still no consensus on this issue. Hence, specifically for the analysis in this study, the possible existence of the EKC is incorporated in the models. Doing so not

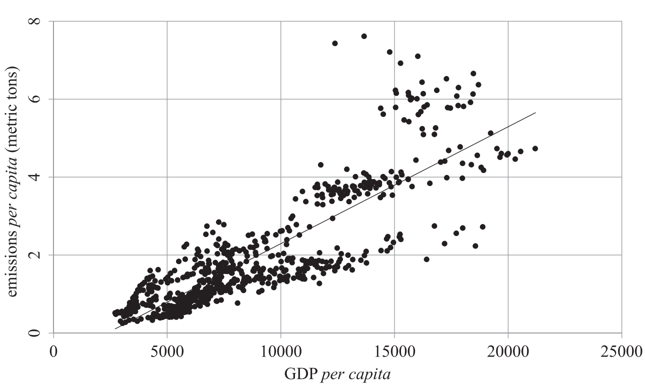

Figure 5. Scatter plot of per capita CO_2 emissions as a function of GDP per capita for the sampled countries in the period 1970–2013 Source: PWT for population data, SWIID for Gini data and ORNL/WDI for emissions data

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only reflects the interest in the EKC itself, but also works as a control for the main hypothesis, that inequality influences CO_2 emissions.

Table 3 shows the results of the four proposed models. All the models proved well specified, passing all the statistical tests recommended by Arellano and Bond (1991)—see the main tests at the bottom of the Table. In the first model, without the inclusion of the variable for inequality, one can observe the existence of the EKC for Latin America, with $\beta_2 > 0$ and $\beta_3 < 0$ proving significant at 1%. However, the average income threshold from which there would be an inflection in per capita CO_2 emissions is very high and implausible. Thus, the result obtained with this model is similar to that of Pablo-Romero and Jesús (2016) and Zilio and Recalde (2011), who found no evidence of the EKC for energy consumption in Latin America and the Caribbean. Regarding this model, it is also worth mentioning the highly significant coefficient of the per capita CO_2 emission from the previous period (β_1), demonstrating the persistent effects of the emissions.

In models (2) and (3), we have the results obtained with the inclusion of the inequality variable. In model (2), although not statistically significant even at 10%, the results point to a negative relation—nonetheless, the existence of the EKC is still identified and significant. It is only when the quadratic form of the Gini index is included that a significant relation between inequality and per capita CO_2 emissions is found: In model (3), we found an inverted U-shaped relationship between those variables ($\beta_4 > 0$ and $\beta_5 < 0$). So depending on the level of the Gini index, a positive or negative impact of it on the CO_2 emissions is observed.

Model (4) offers a more complete and complex picture of the relationships in question, because it simultaneously accounts for the nonlinearities of GDP per capita, the Gini index and the interaction term. This model represents the main contribution of this paper in comparison with the previous literature.

Table 3. Results of the econometric models

	(1)	(2)	(3)	(4)
$c_{i(t-1)}$	0.7389***	0.6975***	0.7008***	0.6838***
	(0.0455)	(0.0663)	(0.0642)	(0.0612)
y_{it}	2.6104***	1.5256**	1.5188**	4.4437***
	(0.6749)	(0.7612)	(0.6967)	(1.4951)
y_{it}^2	−0.1291***	−0.0718*	−0.0714**	−0.1192***
	(0.0348)	(0.0396)	(0.0361)	(0.0394)
g_{it}		−0.0812	6.6680*	19.1581**
		(0.0736)	(3.7890)	(8.6353)
g_{it}^2			−0.8903*	−1.9080**
			(0.4994)	(0.8510)
$y_{it}g_{it}$				−0.5260**
				(0.2592)
Observations	672	560	560	560
Arellano-Bond test order two (p-value)†	0.3568	0.1944	0.1916	0.1898
Sargan test of overidentifying (p-value)††	0.1682	0.3377	0.3870	0.3547

All models are fixed effects for country and year. Standard error in parentheses.
Source: Elaborated by the authors
†H0: no autocorrelation
††H0: overidentifying restrictions are valid.
*significant at 10%.
**significant at 5%.
***significant at 1%.

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All the coefficients in model (4) were statistically significant at 1% or 5%. The persistent effect of emissions (β_1) was as significant as it was in the previous models, proving the robustness of this finding. The signs of the coefficients β_2 and β_3 also suggest the existence of the EKC; while the signs of β_4 and β_5 reveal the same quadratic relationship between inequality and per capita CO_2 emissions found in model (3).

The most interesting aspect of model (4), however, comes to light when all the variables are jointly analysed, including the interaction term. Because we are dealing with variables in logarithmic form, the best way to study the impacts of both GDP per capita and the Gini index on the CO_2 emissions is through the elasticities calculated by Equations (5) and (6).

Equation (6) refers to the idea of the EKC. A positive elasticity means that, at a given level of inequality, an increase in the GDP per capita amplifies the per capita CO_2 emissions; a negative elasticity, on the other hand, means a reduction in CO_2 emissions in response to an increment in the product. The net elasticity we have estimated through model (4) depends on the level of the product as well as on the level of the inequality. Figure 6 illustrates the elasticity of per capita CO_2 emissions in relation to the variation in the GDP per capita for the levels of Gini index between 30.0 and 60.0. The darkest area on the graph portrays positive elasticity, and the brightest area represents negative elasticity.

It is possible to identify a negative elasticity, for example, from the combination of a Gini index higher than 60.0 and GDP per capita higher than US$ 15 000.00 or a Gini index higher than 44.0 associated with a product higher than US$ 30 000.00. Although it is plausible to identify negative elasticities in the graph, there is not a single observation in our sample that meets the combined levels of production and inequality to reach such a result. Put another way the current Latin American scenario of product and income distribution implies that positive economic growth will generate more emissions, *ceteris paribus*. Because the EKC is confirmed in our model, it would be reasonable to argue that the Latin American countries are still on the rising section of the inverted U.

In Figure 7, the results are plotted for the elasticity of per capita CO_2 emissions in relation to the variation of the Gini index for GDP per capita levels ranging from US$ 0.00 to US$ 25 000.00. As in the previous figure, the dark area depicts positive elasticities and the bright area depicts negative elasticities.

The estimated coefficients in model (4) suggest a quadratic relationship between inequality and CO_2 emissions—as well as dependency on the interaction term. Most of

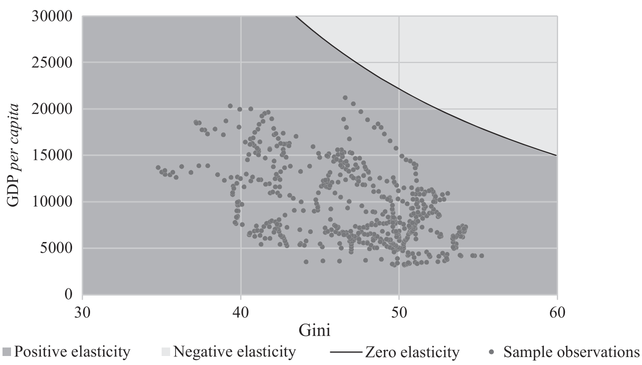

Figure 6. CO_2 emissions elasticity in relation to GDP per capita by Gini index level Source: Elaborated by the authors.

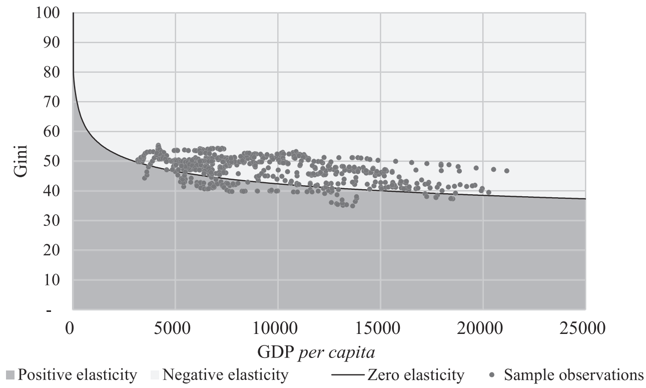

Figure 7. CO_2 emissions elasticity in relation to Gini index by GDP per capita level Source: Elaborated by the authors.

the observation points in our sample lie in the negative elasticity area of the graph. Therefore, Figure 7 illustrates that most of the Latin American countries, during the period of analysis, would face an increment in CO_2 emissions in response to better income distribution if the level of product is held constant.

In comparison with the findings from Grunewald et al. (2017), our results point in the same direction, roughly: higher income inequality is associated with lower CO_2 emissions. However, differently from them, the present study focuses exclusively on a developing region. And because we have estimated elasticities of emissions in relation to both the income inequality and GDP per capita, our results tend to be more sensitive and versatile for regional analysis.

For example, our results show that El Salvador is placed in a situation where deepening the inequality will raise the emissions in the country; on the other hand, worsening the income distribution in Brazil, at its current level of GDP per capita, will diminish the level of emissions. Two developing countries, with quite different economic and demographic structures, can be understood as presenting distinct relationships between domestic product, income inequality and CO_2 emissions.

There are some differences compared with the results from Dorsch and Kirkpatrick (2014), who used the ecological footprint as a dependent variable and had no geographical delimiter. The main hypothesis put forward by the authors is that the EKC might be conditional on the level of inequality. In their work, it was only possible to find the curve at implausibly low levels of inequality. Our results, on the other hand, point out that the EKC may exist at plausible levels of income inequality and GDP per capita, although it was not observed in our sample.

Our results are also similar to those of Knight et al. (2017). Those authors used wealth inequality to determine emission levels for high-income countries and found that higher per capita emissions levels are associated with wealth inequality. For Latin America, we found the same kind of impact but only for lower levels of income inequality, where most of high-income countries in their study would be found.

The results should not be taken as a recommendation to maintain inequality in order to reduce environmental impact, at any level of income. According to Scruggs (1998), although higher levels of inequality are related to lower environmental impacts, it does not mean that environmental sustainability is incompatible with equality. However, our

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analysis indicates that the goals of growth, reduced inequality and environmental sustainability present an even greater challenge for the region.

Regarding the reduction of inequality, the recent literature suggests growth alone will not be enough (Dollar & Kraay, 2002; Kakwani & Pernia, 2000), and in cases of accelerated growth, it may increase the contrast between rich and poor. The results presented here also suggest that growth with reduced inequality could increase environmental pressure in most Latin American cases. A combination of actions will be needed, aimed at reducing inequality and reducing the environmental impact generated by it and by increasing income.

As seen above, the increase in income and reduced inequality led to a large increase in the private vehicle fleet, largely related to the poor quality of public transport, increasing fuel consumption and increasing environmental pressure in the region (Bacerna et al., 2014). Therefore, it would be necessary, for example, to develop more efficient public transport, which could offer a competitive substitute to the use of private vehicles.

Moreover, the increase in average income disproportionately raises energy consumption in Latin America, driven by the use of consumer goods such as household appliances (ECLAC, 2014). Hence, it is essential to improve energy efficiency, which was stagnant in developing countries in the 2000s (Raupach et al., 2007), by ensuring sustainable, efficient and cheap sources. It is also important to improve productivity, incorporating the new knowledge generated by technological innovation, aiming for production oriented towards environmental sustainability, as already is found in developed countries.

6 CONCLUSIONS

Latin America's share of global CO_2 emissions has been increasing since the 1970s, with a growth rates above the world average and the per capita emissions also advancing at a faster pace. Associated with this, there was an increase in average income and, especially since 2000, a reduction in inequality. Reducing inequality can change consumption patterns and power structures and thus influence the level of pollution in the environment.

The theoretical elements regarding the relationship between inequality and environmental impact suggest mechanisms that lead to ambiguous results. This is also the case with the empirical literature on the subject. However, the lack of agreement is mainly because of the fact that different patterns of development have been assessed, revealing that the relationship is complex and highly dependent on the scenario.

The results of this study provide some insights into the relationship between economic growth, income distribution and environmental impact. We have demonstrated quadratic relationships between per capita CO_2 emissions and both GDP per capita and inequality. The nonlinear impact of income inequality is mediated by the level of the GDP per capita—with the direction of the impact depending on the income level. This means that addressing only economic growth or only income distribution is not a reasonable option for most of the Latin American countries.

When planning its development, the region should consider a myriad of policies capable of activating inclusive economic growth. This can be achieved, for instance, by enhancing economic productivity. It is also important to encourage policy making focused on decoupling economic growth from rising CO_2 emissions—this generally points towards education, technology and energy efficiency.

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CONFLICTS OF INTEREST

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