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The determinants of the inequality in CO_2 emissions per capita between developing countries and their implications for environmental policy

Emilio Padilla Rosa[1] | Evans Jadotte[2]

[1]Department of Applied Economics, Autonomous University of Barcelona, Bellaterra, Spain

[2]Macro Economics, Trade and Investment Global Practice, World Bank, Port-au-Prince, Haiti

Correspondence
Emilio Padilla Rosa, Department of Applied Economics, Autonomous University of Barcelona, 08193 Bellaterra, Spain.
Email: emilio.padilla@uab.es

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Abstract

We analyze the differences in CO_2 emissions from fuel combustion per capita between developing countries and how these are influenced by a series of affluence, structural, demographic, and climatic variables. First, a regression analysis provides new evidence on the determinants of CO_2 emissions in developing countries. We find an N-shaped relationship with GDP per capita and a negative impact of the agriculture share and average daily minimum temperatures, while urbanization and the share of potentially active population would be positively correlated with emissions per capita. Second, by using the regression-based inequality decomposition method, we indicate the weight of each significant determinant in explaining the inequality in CO_2 emissions per capita between developing countries. The main contributors are economic affluence and the potentially active population, in this order. We study the relevance of each factor in the changes experienced by inequality over time. Some of our results contrast with previous evidence for more heterogeneous samples. We derive some relevant implications for environmental and energy policy in developing countries.

KEYWORDS

CO_2 emission drivers, CO_2 emission inequality drivers, CO_2 inequality, developing countries, environmental policy, regression-based inequality decomposition, sustainable development

1 | INTRODUCTION

Developing countries have a special interest in the success of global policies to mitigate climate change. First, because according to most projections (IPCC, 2014; Stern, 2006) they will be among the most seriously affected and will suffer the worst expected impacts of climate change. Both their geographical location and their lower resources and capacity to adapt make several developing countries more vulnerable to climate change impacts. Moreover, existing climate change has already disproportionally affected poor countries and contributed to increased economic inequality by slowing, to some extent, the opposite trend that was taking place in recent decades (Diffenbaugh & Burke, 2019). Second, international mitigation agreements involving transfers of resources and technology to low-income countries may also facilitate the development of these countries in a clean (low-carbon) way. Low-income countries may have the opportunity to adopt a low-emission development model, taking advantage of existing technologies already proven in rich countries, and avoid the high-emission development phase experienced by industrialized countries (Padilla, 2017).

The contribution to climate change is highly unequal, with some high-income countries having CO_2 emissions per capita that are twentyfold those of several low-income countries. The unequal contribution to the problem may lead some representatives of developing countries to argue that all the mitigation efforts should be made by those that are more responsible and capable to act. However, an international agreement to mitigate climate change can only be effective with the participation and cooperation of both developed and developing nations. The analysis of the inequality in CO_2 emissions and its driving forces is of great relevance to determine the differences in the degree of responsibility, its trajectory, its causes, as well the fairness and feasibility of different emission distribution agreements. The greater the level of inequality in both emissions and their driving forces, the greater the differences that tend to appear in the criteria on the distribution of mitigation efforts and even on the level of mitigation considered desirable, hampering mitigation agreements. Differences in emissions per capita are driven by factors that follow different trajectories in different countries. The analysis of these drivers and their trajectories over time is crucial to enlighten the debates on policy design and on the criteria to distribute abatement efforts. Moreover, the analysis of the causes of inequality may also shed light on how emissions could be reduced by converging to low emission per capita levels.

Analyses in these areas have typically dealt with CO_2, the most important greenhouse gas. Most studies on the international inequality of CO_2 emissions per capita have focused on the inequality between world nations. Several of them include a decomposition of this inequality. Group decomposition of CO_2 emissions inequality tends to signal that most of the inequality is explained by the inequality between rich and poor groups of countries; either when the groups are directly classified according to income criteria or whether they are geographic regions with different levels of development (Duro & Padilla, 2006; Heil & Wodon, 1997; Padilla & Serrano, 2006). Many researches also include decomposition of inequality indexes based on identity relationships. In short, various studies apply a multiplicative decomposition to split the inequality index across components in order to study the determining factors of the differences in the levels of emissions per capita (such as the Kaya factors in Duro & Padilla, 2006; Padilla & Duro, 2009; who do not include the population factor, since it disappears from the original formulation when emissions per capita are considered). These studies found that the major component of the inequality across countries is the inequality in income (or GDP) per capita between rich and poor countries. The importance of other factors, such as energy intensity or emission intensity of energy, is of a lower magnitude, though still significant both between and particularly, in relative terms, within some country groups (Duro & Padilla, 2006). Therefore, these commented works have aimed both to see the unequal contribution to the environmental pressures of different countries, regions or groups of countries, as well as to ascertain the driving forces of the differences in the levels of per capita emission deriving interesting implications for environmental policy. These studies provide a first picture of inequality and its driving forces but have the limitation of restricting the determinants to the components of the identity used. An alternative appealing method is the application of the regression-based inequality decomposition approach, developed by Fields (2003) for the analysis of income distribution, which was first applied to the international CO_2 inequality by Duro et al. (2017). The main advantage of this method with respect to the previous methods used in this literature is that it enables to test the contribution to inequality of all the factors that are previously identified as relevant determinants of emissions through an econometric regression.

A few analyses on CO_2 emissions distribution have specifically focused on the inequality between developed countries, such as the OECD or the European Union (Padilla & Duro, 2013), to study its evolution and the determinants of this inequality by using the multiplicative decomposition methods mentioned above. Looking more in detail at regions or income groups of countries allows for more precise insights into the reasons for the differences in emissions per capita between countries with a similar level of development (or other common characteristics) and to identify policies that may facilitate the reduction of these differences and of total emissions. The results of this type of analyses may have more practical implications for policy than focusing on the differences between countries with high differences in development and consumption levels per capita, as there may be important heterogeneity in the relevance of the different factors determining emissions for different groups. However, there is no analysis specifically looking at inequality in emissions between developing countries and the causes of these differences. A challenge for coming years is that developing countries advance their development without leading to an impressive increase in emissions, as experienced by some emerging economies. In this context, to ascertain both the determinants of CO_2 emissions per capita in developing countries as well as the causes of the differences in emissions per capita between these countries may help to orientate policies to control emissions growth, follow more sustainable development paths, and fulfill their pledges to control emissions.

In short, we want to take the advantages provided by the regression-based inequality decomposition method developed by Fields (2003) to answer the following research questions: to analyze with an econometric model the economic, structural, demographic, and climate determinants of CO_2 emissions per capita in developing countries (which in our analysis encompasses low and low-middle income countries as defined by the World Bank); to find out how these have changed over time; to analyze the contribution of these factors to the inequality of CO_2 emissions per capita between developing countries; to study the changes in the relative contribution of these factors over time and their causes; to find the contribution of the different factors to the changes in emissions inequality experienced over the period studied; and to extract relevant conclusions for environmental policy from the results obtained. We consider CO_2 emissions from fuel combustion in our analysis.

The rest of the article is organized as follows. Section 2 explains the regression-based inequality decomposition method employed for the analysis of CO_2 emissions inequality between developing countries and describes the variables and data sources used in our analysis.

Section 3 presents and discusses the results. Section 4 gathers the main conclusions of the research.

2 | METHODS AND DATA

As stated above, there are different methodologies to decompose inequality indexes into different components. The traditional decomposition approach (Shorrocks, 1982) consists in decomposing inequality in different additive components. This was later extended to the decomposition into multiplicative factors using the Theil index. The above cited works have adapted and applied these methods to the analysis of environmental pressures inequality, particularly providing useful information for the analysis of international inequality in emissions (Duro & Padilla, 2006, 2011; Padilla & Duro, 2009, 2013; Padilla & Serrano, 2006). These decomposition methods produce useful insights on the inequality in CO_2 emissions per capita between countries and its components. Nevertheless, the techniques described above just assign the contribution to inequality to the components of an identity, which provides a restricted view of the driving factors of emissions. Recent research widened the field of emission inequality analysis by employing the regression-based inequality decomposition method developed by Fields (2003) to study the causes of these inequalities (Duro et al., 2017). In contrast to previous decomposition methods, the regression-based inequality decomposition method does not restrict the components of inequality to the elements of an identity but allows to test the contribution to inequality of any set of relevant factors (Fields, 2003).

We propose the application of the regression-based inequality decomposition methodology to analyze the inequality in CO_2 emissions per capita between developing countries. This methodology requires first to estimate a regression with the determinants of CO_2 emissions per capita, from which we can extract interesting conclusions on the factors that lead to greater or lower emissions in different developing countries and so compare our results with those of the wider literature on the determinants of emissions (such as the environmental Kuznets curve or the STIRPAT literature), and particularly with those works focusing on developing countries.

Following the method described in Fields (2003), we estimate a semi-log linear function of the determinants of our variable of interest, CO_2 emissions per capita:

$$\ln CO_2pc = \alpha + \beta_1 X_1 + \cdots + \beta_K X_K + \varepsilon, \tag{1}$$

where, CO_2pc is the vector of the CO_2 emissions per capita in the different countries considered, and X_i (i = 1, … , K) the vectors of its determinants. We can rearrange it:

$$\ln CO_2pc = \sum_{k=0}^{K+1} \beta_k X_k, \tag{2}$$

where, X_0 is 1, so that $\beta_0 X_0 = \alpha$ is the constant, and β_{K+1} is 1, so that $\beta_{K+1}\, X_{K+1} = \varepsilon$. The method considers the product of the estimated coefficient β_k and its variable X_k as the factor components of CO_2 emissions per capita. The consistent identity formed allows the traditional decomposition methods (Fields, 2003; Shorrocks, 1982).

We take the variances of both sides of the equation. Actually, the variance of logarithms is a commonly used and easily decomposable inequality index (Cowell, 2011; Das & Parikh, 1982):

$$\mathrm{var}(\ln CO_2pc) = \mathrm{var}\left(\sum_{k=0}^{K+1} \beta_k X_k\right). \tag{3}$$

We reorganize it to express the variance of logarithms as the sum of the covariances between each factor component and the dependent variable:

$$\mathrm{var}(\ln CO_2pc) = \sum_{k=0}^{K+1} \mathrm{cov}(\beta_k X_k, \ln CO_2pc). \tag{4}$$

The covariances in (4) are the natural decomposition of the variance. We can then obtain the relative contribution of each factor component:

$$s_k(\ln CO_2pc) = \frac{\mathrm{cov}[\beta_k X_k, \ln CO_2pc]}{\mathrm{var}(\ln CO_2pc)}, \tag{5}$$

where, s_k is the share of the contribution of factor k to the inequality in CO_2 emissions per capita.

The regression can be done for different periods, so that the relative contribution of each factor to inequality may change over time. Then, the method also allows to check whether the changes in s_k over time are caused by changes in the dispersion of factor k (the inequality of the factor across countries) or by changes in its coefficient β (i.e., its importance of the factor in determining CO_2 emissions according to the regressions):

$$\begin{aligned} s_{kt} - s_{kt-1} &= \frac{\mathrm{cov}\left(Z_t^k, \ln CO_2pc_t\right)}{\mathrm{var}(\ln CO_2pc_t)} - \frac{\mathrm{cov}\left(Z_{t-1}^k, \ln CO_2pc_{t-1}\right)}{\mathrm{var}(\ln CO_2pc_{t-1})} \\ &= \left[\frac{\mathrm{cov}\left(\widehat{Z}_{t-1}^k, \ln CO_2pc_t\right)}{\mathrm{var}(\ln CO_2pc_t)} - \frac{\mathrm{cov}\left(Z_{t-1}^k, \ln CO_2pc_{t-1}\right)}{\mathrm{var}(\ln CO_2pc_{t-1})}\right] \\ &\quad + \left[\frac{\mathrm{cov}\left(Z_t^k, \ln CO_2pc_t\right)}{\mathrm{var}(\ln CO_2pc_t)} - \frac{\mathrm{cov}\left(\widehat{Z}_{t-1}^k, \ln CO_2pc_t\right)}{\mathrm{var}(\ln CO_2pc_t)}\right], \end{aligned} \tag{6}$$

where, $Z_t^k = \beta_{kt} X_{kt}$ and $\widehat{Z}_{t-1}^k = \beta_{kt-1} X_{kt}$. We can denote as *dispersion effect* the first term of the right-hand side, since the coefficients do not change between $t-1$ and t (only the dispersion varies). That is, the effect associated to the changes in the factor inequality. We can denote as *coefficient effect* the second term, since the dispersion of vector X_k does not change (only the coefficient varies). That is, the effect associated to the changes in the coefficients according to the regressions estimated.

Finally, we can also measure the contribution of factor k to the total variation in CO_2 emissions per capita inequality between period $t-1$ and period t as:

$$\delta_k \equiv \frac{s_{kt} I(.)_t - s_{kt-1} I(.)_{t-1}}{I(.)_t - I(.)_{t-1}}, \tag{7}$$

where, $I(.)_t$ is the inequality in CO_2 emissions per capita of period t. This expression can be applied to any inequality index. In coherence with the Fields (2003) regression-based inequality decomposition methodology employed, we use the logarithmic variance in our factorial decomposition, which is a commonly used inequality index that is decomposable (Das & Parikh, 1982), and is scale invariant (Cowell, 2011), and so seems an appropriate choice for our analysis.

The data required for our analysis have been taken from the World Bank database (https://data.worldbank.org/). Given data availability, we had to limit our analysis to the period 1995–2014 for which we had a consistent set of developing countries, with minimum variations in the yearly sample, with data for all the required variables (see the list of countries included in the Table A4 of the Appendix A). Taking a previous year as the initial year of our analysis involved using a much reduced sample which, as we checked, would have led to a pattern in the evolution of inequality for those previous years just caused by the different countries included in the sample.

The dependent variable employed in our analysis, ln CO_2pc_i is measured as the logarithm of the kilograms of CO_2 emissions from fuel combustion per capita. As for the independent variables that resulted significant and so were included in the final estimated model, these are: $GDPpc_i$, the GDP per capita (in constant 2010 US$); $Agriculture\_sh_i$, the value added of agriculture, forestry and fishery as a percentage of country GDP; $Urbanization_i$, the urban population as a percentage of total population; $Pop15–64_i$, the population of ages 15–64 as a percentage of total population; and $tmin_i$, the climate normal, that is, a 30 years average, for minimum daily temperatures in the country, in °C. Other economic, demographic and climate variables were tested, but were not found significant, such as the share of industry on total GDP, trade openness, population density, household members or the average maximum daily temperatures in the country. These variables were discarded in the final estimated models to allow the subsequent correct decomposition of inequality with the above indicated method into the contribution of all significant variables. Table 1 shows the descriptive statistics of the variables employed in the estimation.

3 | RESULTS

Figure 1 shows the trajectory of the inequality in CO_2 emissions per capita between developing countries for the period analyzed as computed by the variance of the logarithm in CO_2 emission per capita.

There is a decrease of this inequality between 1995 and 2000 and a slight increase between 2000 and 2005; then, the inequality decreases during the rest of the analyzed period, being this reduction quite sharper since 2010. We are particularly interested in understanding the reasons of this decrease in the inequality in CO_2 emissions experienced since 2005. The decrease in inequality concentrates in the last years of the period, which clearly contrasts with other findings in the literature for the international inequality in CO_2 emissions per capita that considered both developing and developed countries, since they found an important decrease much before 2005 (Duro & Padilla, 2006; Heil & Wodon, 1997; Padilla & Serrano, 2006).

During this same period the emissions per capita of developing countries experienced an important increase. In order to see how this increase was distributed among the different countries, we show how the different quartiles changed in Table 2, as the distributive consequences of this increase are different whether the greater increases were concentrated in lower emitters or in those developing countries emitting above the median.

Table 2 shows that the reduction in inequality has been particularly driven by the greater increase in emissions per capita in the first quartile of the distribution with respect to the other quartiles. In addition, while the minimum value experiences a great increase, there is a reduction in the maximum value of the sample. When talking about emissions per capita, an ideal situation would apparently be one in which all countries converge to lower values, which is not the case, as all quartiles (but the maximum value) increase in the period. However, we have to take into account that some low income countries depart from very low levels of CO_2 emissions per capita, so we cannot see that increase in the lower values as a necessarily negative outcome—given the strong link existing between economic development, energy consumption and CO_2 emissions—but as the result of a parallel economic development process experienced during the period. In this sense, our main interest in this research is to investigate the contribution to CO_2 emissions inequality of different factors and how has it changed over time.

The decomposition of emissions inequality with the regression-based inequality decomposition approach will provide information on the reasons behind this inequality, including factors beyond those that could be included in simpler accounting decomposition approaches. Moreover, it will provide information on the importance of these factors for the particular case of developing countries, which will allow for comparison with results for other samples of countries.

3.1 | The determinants of CO_2 emissions per capita in developing countries

As stated in the methods section, our method requires, first, to estimate the determinants of CO_2 emissions per capita. In this respect, our analysis will contribute to the analysis of the determinants of these emissions in developing countries. The variables employed are those that the literature has identified as relevant drivers for CO_2 emissions in the environmental Kuznets curve (Dinda, 2004; Grossman & Krueger, 1991; Shahbaz & Sinha, 2019) or the STIRPAT literature (York et al., 2003). The comparison with studies which also focus on developing countries is of particular interest for our analysis.

TABLE 1 Descriptive statistics of the variables

Variable	Mean	Median	Stand. Dev.	Max.	Min.	Obs.
1995						
ln CO_2pc_i	5.76	5.93	1.26	9.07	2.75	65
$GDPpc_i$	1037.92	870.30	677.95	2938.89	183.55	65
$Pop15–64_i$	53.38	52.46	3.85	66.60	46.62	65
$Urbanization_i$	32.03	31.84	14.25	66.95	7.21	65
$Agriculture\_sh_i$	28.07	27.30	12.06	56.54	6.65	65
$tmin_i$	16.20	18.90	7.05	25.30	−7.70	65
2000						
ln CO_2pc_i	5.78	5.82	1.23	8.78	2.85	67
$GDPpc_i$	1091.10	845.98	726.13	3117.82	197.43	67
$Pop15–64_i$	54.75	53.84	4.58	69.08	47.43	67
$Urbanization_i$	33.93	32.98	14.24	67.15	8.25	67
$Agriculture\_sh_i$	26.14	24.99	12.88	76.07	5.30	67
$tmin_i$	16.28	18.90	6.96	25.30	−7.70	67
2005						
ln CO_2pc_i	5.78	5.82	1.23	8.78	2.85	67
$GDPpc_i$	1091.10	845.98	726.13	3117.82	197.43	67
$Pop15–64_i$	54.75	53.84	4.58	69.08	47.43	67
$Urbanization_i$	33.93	32.98	14.24	67.15	8.25	67
$Agriculture\_sh_i$	26.14	24.99	12.88	76.07	5.30	67
$tmin_i$	16.28	18.90	6.96	25.30	−7.70	67
2010						
ln CO_2pc_i	6.00	6.01	1.22	8.80	3.20	68
$GDPpc_i$	1410.50	1170.28	985.02	4168.51	234.24	68
$Pop\ 15–64_i$	57.43	55.87	6.10	73.34	47.46	68
$Urbanization_i$	38.60	36.77	15.34	68.60	10.64	68
$Agriculture\_sh_i$	22.41	22.01	11.59	52.94	3.83	68
$tmin_i$	16.10	18.60	7.02	25.30	−7.70	68
2014						
ln CO_2pc_i	6.17	6.29	1.13	8.87	3.80	68
$GDPpc_i$	1574.82	1297.45	1082.86	4578.29	245.33	68
$Pop\ 15–64_i$	58.16	56.39	6.22	74.20	47.20	68
$Urban\ pop_i$	40.25	39.39	15.74	69.21	11.78	68
$Agriculture\_sh_i$	21.09	19.99	10.63	51.79	4.83	68
$tmin_i$	16.10	18.60	7.02	25.30	−7.70	68

Note: ln CO_2pc_i measured as the logarithm of the kilograms of CO_2 emissions from fuel combustion per capita; $GDPpc_i$ measured in constant 2010 US$; $Agriculture\_sh_i$, measured as a percentage of country GDP; $Urbanization_i$ and $Pop15–64_i$ measured as percentages of total population; and $tmin_i$, measured as 30 years average, for minimum daily temperatures in the country, in °C.
Source: Prepared by the authors with World Bank data.

Table 3 shows the results for the ordinary least squares estimations for the selected years. The model shows a high goodness of fit, as the explanatory variables used in our estimated model explain above 83% of the inequalities in CO_2 emissions per capita between developing countries. All variables included are significant for all years, except for two variables for a couple of years ($Agriculture\_sh_i$ for years 2000 and 2005 and $Urbanization_i$ for years 1995 and 2000). However, these variables also show signs and coefficient magnitudes for these years that are consistent with those estimated for the rest of years considered. All significant variables included in the model show the expected signs, or signs that are consistent with previous findings in the literature, and the VIF test showed no multicollinearity problems. Besides the variables finally included in the model, we tested other economic, demographic and climate variables. In short, as regards climate variables, we also tested the climate normal for the maximum daily temperature; as regards demographic variables, we also tested the variables population density and average household members; as regards economic variables, besides the share of agriculture, we also tested the impact of the share of industry and trade openness. These variables were not significant, so we discarded them from the model estimated as a basis of our later decomposition in order to be able to apply the decomposition method consistently. We comment below the justification for testing the different variables and the results obtained in each case. As the main concern of our analysis is the decomposition of the inequality in CO_2 emissions per capita, and for reasons of space, we do not provide all the results with the variables that were not significant (or showed in the main text, but just provide the results of the chosen model with significant variables that will allow the later decomposition). The results of the regressions including these variables are available in the Tables A1–A3 of the Appendix A.

The coefficients of the semi-log model are interpreted as semi-elasticities. That is, an increase of one unit in the value of any independent variable leads to a β% increase in the CO_2 emissions per capita. As regards GDP per capita, the results indicate a cubic relationship with CO_2 emissions per capita, as the coefficients of the quadratic and cubic variable are significant, though small. That is, the data supports an N-shaped form for the cross-country relationship between CO_2 emissions per capita and GDP per capita. This same pattern was previously found by other authors for different sets of countries and periods (Alshubiri & Elheddad, 2019; Duro et al., 2017; Halicioglu, 2009; Martínez-Zarzoso & Bengochea-Morancho, 2003, 2004; Moomaw & Unruh, 1997; Shafik, 1994). The absolute value of the coefficients of GDP in our estimation are higher than those found in a previous study also employing a semi-log estimation for a sample including both developed and developing countries (Duro et al., 2017), so that income is more relevant in determining the level of emissions for our sample. However, the results in the literature are mixed and other papers just found a positive monotonic relationship (see e.g., Shafik & Bandyopadhyay, 1992; or Roca et al., 2001), while many others found support for the environmental Kuznets curve hypothesis for CO_2 emissions, that is, an inverted-U shaped relationship (Cole et al., 1997; Holtz-Eakin & Selden, 1995) (see Shahbaz & Sinha, 2019, for an extended review of the literature on the issue). These mixed results may derive from different model specifications, estimation methodologies, sample of countries and periods analyzed.

Therefore, though economic affluence has a clear impact on emissions, being a positive correlation between them for the lower and the higher part of the income per capita distribution, our results show that, for a segment of the income per capita distribution of countries, the relationship changes its sign, which is a consistent result across the different years estimated. In any case, as Cole (1999, p. 96) states, "the impact of economic development on the environment is clearly complex in nature. It is important to note, however, that whilst economic growth may facilitate some environmental improvements, this is not an automatic process and will only result from investment and policy initiatives." Our result just shows the relationship between CO_2 emissions per capita and GDP per capita for a cross-section of countries in different moments of time and should not be interpreted as predicting the path that will be followed by the different individual countries as their income changes over time (Piaggio & Padilla, 2012). If the objective was to predict the behavior of countries, which is not the case here, the research should be based on longitudinal studies on

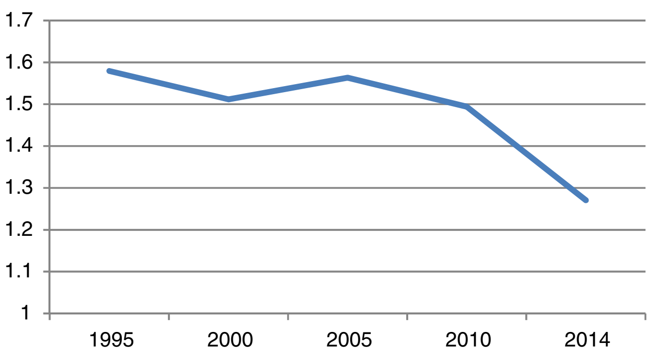

FIGURE 1 Inequality in CO_2 emissions per capita between developing countries, 1995–2014. *Source*: Prepared by the authors with World Bank data [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Quartiles of the distribution of CO_2 emissions per capita between developing countries, 1995–2014

Quartile		1995	2000	2005	2010	2014	Change 1995–2014
0	(Min. value)	0.016	0.017	0.021	0.025	0.045	184.8%
0.25	(Q1)	0.120	0.148	0.158	0.187	0.220	83.3%
0.5	(Q2 or median)	0.377	0.335	0.284	0.406	0.531	40.8%
0.75	(Q3)	0.702	0.765	0.986	0.975	1.058	50.7%
1	(Max. value)	8.657	6.526	7.088	6.641	7.088	−18.1%

Note: the value in the first column denotes the share of countries with CO_2 emissions (*t*) per capita below the value of the other columns for each year. The first row shows the minimum value of CO_2 emissions per capita across developing countries for each year. The last row shows the maximum value of CO_2 emissions per capita across developing countries for each year. The three rows in the middle show the values separating the quartiles of the distribution of CO_2 emissions per capita between developing countries. Notice that CO_2 emissions are considered here in levels, while Table 1 included them in logarithms as in the estimation.
Source: Prepared by the authors with World Bank data.

TABLE 3 Cross-section regressions on the determinants of CO_2 emissions per capita in developing countries, selected years (1995–2014)

	1995	2000	2005	2010	2014
Economic affluence					
$GDPpc_i$	0.0043087***	0.0051087***	0.0041723***	0.002815***	0.0023652***
	(0.0011882)	(0.0009592)	(0.0007637)	(0.0007467)	(0.000612)
$GDPpc^2{}_i$	−2.25e−06**	−2.70E−06***	−2.02E−06***	−1.12E−06***	−8.82E−07***
	(9.23e−07)	(7.01e−07)	(4.67e−07)	(3.80e−07)	(2.96e−07)
$GDPpc^3{}_i$	3.58e−10*	4.53E−10***	3.06E−10***	1.42E−10**	1.07E−10**
	(2.09e−10)	(1.48e−10)	(8.51e−11)	(5.84e−11)	(4.25e−11)
Economic structure					
$Agriculture\_sh_i$	−0.0182897**	−0.010126	−0.0107789	−0.017622**	−0.0173629**
	(0.0082313)	(0.0067682)	(0.0069369)	(0.008562)	(0.0077447)
Demography					
$Urbanization_i$	0.0109378	0.0049553	0.0167026***	0.0138178**	0.0128213***
	(0.0067653)	(0.0062471)	(0.0058792)	(0.0053484)	(0.0047432)
$Pop15–64_i$	0.1023719***	0.0941024***	0.0860454***	0.067435***	0.0552043***
	(0.0233102)	(0.0179294)	(0.0153804)	(0.0145942)	(0.0128721)
Climate					
$tmin_i$	−0.0510659***	−0.0409441***	−0.0206693**	−0.0185509*	−0.0321508***
	(0.010571)	(0.0102079)	(0.0101873)	(0.0108914)	(0.0095407)
Intercept	−0.7600811	−1.097137	−1.190788	0.4932817	1.674291**
	(1.392212)	(1.011626)	(0.9082756)	(0.8935976)	(0.80962)
N	65	67	68	68	68
F	40.54***	43.19***	47.95***	41.92***	44.95***
R^2	0.8327	0.8367	0.8484	0.8303	0.8398
Adjusted R^2	0.8122	0.8173	0.8307	0.8105	0.8212

Note: Statistical significance is denoted by (*) at the 10% level ($p < .10$); (**) at the 5% level ($p < .05$); and (***) at the 1% level ($p < .01$). Standard errors within parentheses.
Source: Prepared by the authors with World Bank data.

individual countries (De Bruyn et al., 1998; Moomaw & Unruh, 1997; Roca et al., 2001).

As regards economic structure, we first tested two variables of production composition, the share of agriculture value-added on total GDP and the share of industry value-added on total GDP, while we left services as the base sector. The expected sign in the case of the latter variable was positive, as a greater share of industry is usually expected to be associated, other things equal, to more energy intensive sectors and so correlated with higher emissions, while in the case of agriculture we expected the contrary to hold. However, in the case of the industry share, the coefficient was not significant for any of the years of the sample. That is, for developing countries and the years analyzed there is not a significant impact in emissions where the share of industry on GDP increases (across countries) reducing the share of services. Moreover, for the last years of the sample (2010 and 2014) the non-significant coefficient was even negative. This may seem a surprising result, and actually contrasts with the results obtained by Duro et al. (2017) with a similar methodology and model for a sample of countries that also included developed countries. The share of industrial sectors was also found as significant in other studies for the case of China (Shen, 2006) or Uruguay (Piaggio et al., 2017). There are various explanations for our outcome. Service and industrial sectors are to a certain extent complementary sectors that use to grow together in low income countries. The idea that the service sector is a clean sector ignores that, besides the high direct emissions of the transport activity, other service activities, on top of their direct energy consumption, require other sectors, from which they purchase intermediate goods, to consume energy and materials. Several studies contradict the misperception of the service sector as a non-material sector (Alcántara & Padilla, 2009; Fourcroy et al., 2012; Gadrey, 2010; Nansai et al., 2009; Piaggio et al., 2015; Rosenblum et al., 2000; Suh, 2006). According to Gadrey (2010) a larger share of the service sector in the economy leads to more energy consumption. Friedl and Getzner (2003) found the share of services to be positively correlated with greater emissions for the case of Austria. Our results would be consistent with those findings, as they indicate that a 1% increase in the share of agriculture, meaning a decrease in the joint share of industry and services, would lead to a significant decrease of emissions (between 1% and 1.8%, according to the year). Finally, we also tested trade openness (measured as the ratio of the sum of exports and imports on GDP). It only appeared significant for the year 1995, with a very low positive value, being far from significant for the other years, so we discarded the variable from the model. When using the variable as just the percentage of exports on GDP the coefficient was not significant for any year. This result would be consistent with for example, the results of Cole et al. (1997), which seems to be also the most common result for other pollutants than CO_2 (Grossman & Krueger, 1991). It is also consistent with the result of Lamb et al. (2014) who found that trade openness (measured just as the percentage of exports on GDP) was not a significant determinant of territorial emissions for a set of 87 countries for the year 2008, though they found it significant with a positive coefficient when consumption-based emissions were employed instead. The variable was neither significant in the analysis of Sharma (2011) for a panel of 69 countries. In contrast, Shahbaz et al. (2017) found that trade openness had a positive significant impact on CO_2 emissions per capita for a panel of 107, with results that hold also for subpanels of low, middle and high income, while for individual countries the coefficient was negative or positive depending on the country. Chang et al. (2014) also found that the ratio of net exports had a positive impact on carbon footprint per capita for a panel of 98 countries. In contrast, Atici (2009) found trade openness to be negatively correlated with emissions in Central and Eastern Europe. Some individual country studies have found trade openness to have a negative relation with CO_2 emissions, such as Piaggio et al. (2017) for Uruguay and Friedl and Getzner (2003) for Austria, while others have found the opposite, such as Halicioglu (2009) for Turkey, which would depend on the specific trade composition and openness processes followed in these different countries. As indicated above, the fact that our cross-national analysis does not find this coefficient as significant, does not mean that the variable may not have an impact on the evolution of the emissions of some individual countries over time, as the literature suggests that may be the case.

With respect to the coefficients of demographic variables, the percentage of population aged 16–64, $Pop16\text{–}64_i$, shows a significant positive value for all years, meaning that an additional 1% of working age population (with respect to total population) is associated with around 10% more emissions at the beginning of the period, but just 5.5% at the end. This result is in line with the results of Duro et al. (2017) for a sample of both developing and developed countries. Cole and Neumayer (2004) also found that population aged 15–64 was a significant determinant of CO_2 emissions, though only when they did not include in the model urbanization and household members, while the variable was not significant otherwise; though in their case they used total instead of per capita CO_2 emissions, which may explain some differences in their results. This population segment is the potentially active population, which according to our results seems associated with more polluting habits and consumption patterns. The coefficient, however, seems to decline over time, though maintaining its significance.

As regards the other demographic variable included in the final model, a (1%) increase in urban population with respect to total population, $Urbanization_i$, is associated with (above 1%) greater CO_2 emissions per capita and the coefficient is significant for most years of the sample. This result is consistent with the previously found by Jones (1991) and Parikh and Shukla (1995) for cross-section analyses for developing countries, and Cole and Neumayer (2004) and Duro et al. (2017) for samples with developing and developed countries (though in our analysis on developing countries we find greater coefficients since 2005 that this last work). However, the results in the literature are mixed and, for example, Hossain (2011) found that this variable had different impacts on different countries for a set of newly industrialized countries. Sharma (2011) and Balsalobre-Lorente et al. (2022) found a negative effect of urbanization on CO_2 emissions per capita for a panel of 69 countries and for BRICS countries, respectively. Urban habits and infrastructures may be associated with more energy consumption, more use of fossil fuels instead of biomass (emissions from biomass are not considered), longer displacements for commuting and buying and more use of motor vehicles (Cole & Neumayer, 2004; Parikh & Shukla, 1995). However, there are also other effects such as more technical innovation, energy and land use efficiency and access to information which may in the long run help to decrease emissions (Jiang & Hardee, 2011), which would explain the mixed results of the impact of urbanization on CO_2 emissions. Lamb et al. (2014) found that urbanization was a significant determinant of emissions, though only with the usual territorial-based emissions but not with consumption-based carbon emissions. In our estimation for developing countries there is a clear positive relationship between urbanization and CO_2 emissions, which, as stated above for other determinants, does not mean that this relationship could predict the relationship over time of the individual countries of the sample.

We checked other demographic variables but found that they were not significant. In short, we tested for the impact of average household size on CO_2 emissions per capita but found no significant influence. The variable has been suggested to impact on resource consumption and CO_2 emissions (Liu et al., 2003; MacKellar et al., 1995). Cole and Neumayer (2004) found that this variable was significant and negatively correlated with CO_2 emissions (their dependent variable was not in per capita terms). According to our results, however, it does not seem to have a significant impact on the CO_2 emissions per capita of developing countries. We also tested for population density, which has often been included in the analysis of the determinants of several environmental pressures and the impact of which is ambiguous in the literature. Onafowora and Owoye (2014) found a significant and positive influence on CO_2 emissions in Brazil, China, Egypt, Japan, and Mexico, while in the other countries they considered (South Korea, Nigeria, and South Africa) the impact on CO_2 emissions was statistically insignificant. Lamb et al. (2014) found that population density was not a significant determinant of carbon emissions (neither for consumption- or territorial-based carbon emission). Our results are consistent with this last paper, as the coefficient of population density was far from being significant for any of the years.

Concerning climate variables, we included the average minimum daily temperature in the model, as colder temperatures are associated with greater heating requirements (Neumayer, 2002), and so greater CO_2 emissions from fuel combustion. We also checked the impact of the average maximum daily temperature. This variable is, obviously, highly correlated with the average minimum daily temperature tested in our model; however, the later was more significant and for more years than the former, so we just left the minimum daily temperature in the model, in line with the related literature. The variable was significant and negatively associated with CO_2 emissions per capita for all years. In short, a country with an average minimum daily temperature 1°C below others would be statistically associated with 5% more emissions per capita in 1995 but just 3.2% in 2014. York et al. (2003), Neumayer (2002, 2004), Lamb et al. (2014) and Duro et al. (2017) also found this influence of colder temperatures for samples including both developing and developed countries, though we find a bit larger impact of this variable for developing countries.

3.2 | Decomposition of the inequality in CO_2 emissions per capita between developing countries

Following expression (5), we use the coefficients estimated, together with the dispersion of each variable to determine the contribution of each factor to the inequality in CO_2 emission per capita between developing countries that are shown in Table 4. In addition, expression (6) allows for the decomposition of the change experienced between each period in the relative contribution of each factor into the coefficient effect (due to the change in the relationship between the variable and CO_2 emissions as shown by the coefficients in the regressions) and the dispersion effect (due to the inequality in the variable between countries), which is shown in Table 5.

The component that contributed most to the inequality in CO_2 emissions per capita was economic affluence (which aggregates the contribution of the different GDP variables), with a contribution over 30% for all the years analyzed. The factor increased its contribution significantly between 1990 and 2000, when it reached its maximum relative contribution (41.1%), but decreased in the next 10 years to end the period with a similar contribution to that at the beginning. Comparing the results with the ones of Duro et al. (2017), who included both developed and developing countries, we find that, for developing countries there is a significantly greater relative contribution of affluence to emissions inequality (almost double for the years 1995 and 2005, which were also included in their sample). Duro and Padilla (2006) and Padilla and Duro (2013) also found that income inequality was the main driver of CO_2 emissions per capita inequality. The first paper applied a multiplicative decomposition of inequality into the factors of the Kaya identity for a world sample, finding that affluence was responsible for up to 60% of emissions inequality, while the second applied it to the European Union countries (a more income-homogeneous sample) and found that, though at the beginning of the period (1990) energy intensity was more important (due to the energy inefficiency of the eastern countries), at the end, affluence clearly was the main determinant of emissions. Contrary to our method, these two studies restrict the factors to those of the Kaya identity and impose the same elasticity to them, while our methodology allows for the inclusion of any influencing factor, allowing a better determination of the impact of affluence on total inequality in CO_2 emissions per capita. As regards the explanation of the changes in the relative contribution over time, taking the whole period we can see that the small increase in the relative contribution of this variable is caused by the dispersion effect (i.e., income inequality), which goes in the opposite direction of the coefficient effect (Table 5). Therefore, the persistence of significant differences in per capita income between developing countries—particularly its trajectory between 1995 and 200—would explain why per capita income continues to be the main explanatory factor of inequality in CO_2 emissions per capita between developing countries at the end of the period.

With reference to the sectoral composition of production, the share of agriculture on GDP accounts for above 10% of inequality in emissions, though it is slower for 2000 and 2005. The small change in its relative importance between the beginning and the end of period would be mainly explained by the dispersion effect (Table 5). However, looking at the sub-periods, we see that there has not been a constant tendency in the contribution of the different effects to the changes experienced in the relative contribution of this factor between the sample years. Actually, while the coefficient (β) estimated at the end of the period is very similar to the one in 1995, it decreases significantly between 1995 and 2000, which is caused by the coefficient effect; that is, the lower relevance of the factor in explaining CO_2 emissions per capita. The contribution of agriculture to inequality is lower than the one found by Duro et al. (2017) for their more heterogeneous sample (the share of this sector is generally greater for developing countries, than for the world average). In any case, the relevance of this variable, together with the fact that the

TABLE 4 Factor contribution to the inequality in CO_2 emissions per capita between developing countries (%)

	1995	2000	2005	2010	2014
Affluence$_i$	30.9%	41.1%	35.1%	31.7%	32.1%
Agriculture_sh$_i$	10.4%	5.6%	6.3%	11.7%	11.1%
Urbanization$_i$	8.2%	3.3%	12.3%	10.0%	9.6%
Pop15–64$_i$	20.7%	24.1%	27.1%	24.5%	22.3%
tmin$_i$	11.5%	8.5%	3.3%	3.3%	7.6%
Residual	18.3%	17.5%	15.9%	18.7%	17.3%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Source: Prepared by the authors with World Bank data.

TABLE 5 Changes in the relative contribution of each factor and decomposition into coefficient and dispersion effects

	Absolute contribution change	Dispersion effect	%	Coefficient effect	%
1995–2000					
Affluence$_i$	0.1011	0.0099	10%	0.0912	90%
Agriculture_sh$_i$	−0.0485	−0.0035	7%	−0.0449	93%
Pop15–64$_i$	0.0339	0.0551	162%	−0.0211	−62%
Urbanization$_i$	−0.0484	−0.0080	17%	−0.0404	83%
tmin$_i$	−0.0301	−0.0092	30%	−0.0209	70%
Residual	−0.0080	−0.0080	100%	0.0000	0%
2000–2005					
Affluence$_i$	−0.0600	−0.0013	2%	−0.0586	98%
Agriculture_sh$_i$	0.0071	0.0032	46%	0.0038	54%
Pop15–64$_i$	0.0304	0.0558	183%	−0.0254	−83%
Urbanization$_i$	0.0897	0.0031	3%	0.0866	97%
tmin$_i$	−0.0512	−0.0184	36%	−0.0328	64%
Residual	−0.0159	−0.0159	100%	0.0000	0%
2005–2010					
Affluence$_i$	−0.0332	0.0077	−23%	−0.0409	123%
Agriculture_sh$_i$	0.0540	0.0086	16%	0.0453	84%
Pop 15–64$_i$	−0.0256	0.0421	−164%	−0.0677	264%
Urbanization$_i$	−0.0232	−0.0023	10%	−0.0209	90%
tmin$_i$	−0.0004	0.0034	−974%	−0.0038	1074%
Residual	0.0284	0.0284	100%	0.0000	0%
2010–2014					
Affluence$_i$	0.0038	0.0150	394%	−0.0112	−294%
Agriculture_sh$_i$	−0.0062	−0.0046	74%	−0.0016	26%
Pop15–64$_i$	−0.0224	0.0270	−121%	−0.0494	221%
Urbanization$_i$	−0.0041	0.0033	−81%	−0.0074	181%
tmin$_i$	0.0429	0.0108	25%	0.0322	75%
Residual	−0.0140	−0.0140	100%	0.0000	0%
1993–2014					
Affluence$_i$	0.0117	0.0872	744%	−0.0755	−644%
Agriculture_sh$_i$	0.0063	0.0122	193%	−0.0059	−93%
Pop15–64$_i$	0.0163	0.2069	1267%	−0.1905	−1167%
Urbanization$_i$	0.0139	−0.0002	−1%	0.0141	101%
tmin$_i$	−0.0388	0.0060	−15%	−0.0447	115%
Residual	−0.0096	−0.0096	100%	0.0000	0%

Source: Prepared by the authors with World Bank data.

share of industry on GDP was not significant, clearly reinforces the notion that agriculture is the least polluting sector and that both service and industry are associated with more emissions than the agriculture sector for developing countries, which is reflected in the 10%–11% contribution of agriculture to emissions inequality between developing countries.

Urbanization contributes around 10% to emissions inequality between developing countries, and the contribution at the end of the period is just slightly greater than at the beginning. Since 2000, this factor is more relevant (about the double) in explaining inequality between developing countries than it is in explaining total inequality, if we compare our results with Duro et al. (2017). The slight increase in its relative contribution in the period is mainly explained by the coefficient effect; that is, it becomes relatively more important in explaining CO_2 emissions from fossil fuels per capita over time.

The other demographic variable, population aged 15–64, is the second most relevant variable in explaining inequality in CO_2 emissions per capita between developing countries, with a contribution that is always above 20%. The relevance of this factor was also found by Duro et al. (2017), but for their sample of countries it was found as

TABLE 6 Contribution of the different factors to the change in CO_2 emissions inequality (%)

	1995–2000	2000–2005	2005–2010	2010–2014	1995–2014
Affluence$_i$	−193.9%	−139.6%	106.7%	29.6%	26.1%
Agriculture_sh$_i$	118.2%	26.8%	−110.3%	15.2%	7.8%
Pop15–64$_i$	115.9%	273.4%	62.4%	12.3%	2.5%
Urbanization$_i$	−54.8%	115.7%	82.4%	37.2%	14.0%
tmin$_i$	78.4%	−145.8%	4.1%	−21.1%	27.4%
Residual	36.1%	−30.5%	−45.4%	26.7%	22.2%
Total	100.0%	100.0%	100.0%	100.0%	100.0%
Inequality change	−4.3%	3.4%	−4.4%	−15.0%	−19.6%

Source: Prepared by the authors with World Bank data.

the main factor, while for developing countries, though very important, is still clearly below the contribution of affluence. The relative importance of this factor fluctuates over the period, increasing significatively until 2005 and decreasing thereafter, though its relative contribution is always below the contribution of affluence. The small increase in its relative importance over the whole period is explained by the dispersion effect; that is, the increase would be explained by the trajectory of the differences in population aged 16–64 between developing countries. Meanwhile, the coefficient effect may have played in the opposite direction, as the coefficient estimated for this variable decreased significantly during the period; that is, it became relatively less important in determining emissions (Table 3). In fact, it is noticeable the strong movement in opposing directions of both effects.

The average daily temperature contribution to inequality decreases during the period, though at the end of the period it still explains 7.6% of the inequality. The decrease in its relative importance in explaining inequality is mainly caused by the coefficient effect; that is, the fact that temperatures are a bit less relevant (lower absolute coefficient) in explaining CO_2 emissions per capita from fossil fuels at the end of the period.

The residual contribution is quite stable over the period (between 15.9% and 18.7%). It may be gathering the impact of several omitted determinants, such as different technological levels, institutional differences, social factors, and others for which we do not have available and suitable data for all countries and years. In any case, there are not relevant changes in the contribution of this factor during the period, so the potentially omitted variables may not change our conclusions as regards the evolution in the influence of the significant factors considered.

Finally, Table 6 indicates the percentage contribution of the different variables to the change in inequality over the period, computed with expression (7). All the factors contributed to the reduction in inequality between developing countries experienced over the period, either because of the evolution of their own inequality as for the changes in their influence on emissions, as shown by previous tables.

It can be highlighted the contribution of affluence to the reduction in the inequality in CO_2 emissions per capita from fuel combustion. This factor was responsible for 26.1% of this decrease. In any case, its contribution to the reduction is slightly below its global contribution to the inequality of CO_2 emissions per capita between developing countries, which explains that at the end of the period affluence explains a slightly larger share of the total inequality of CO_2 emissions per capita than at the beginning. In this case, the trajectory of the inequality in affluence between developing countries has impeded an even greater reduction of the inequality in CO_2 emissions per capita.

It is particularly noticeable the contribution to the reduction of CO_2 emissions per capita inequality of average daily temperatures, with a contribution to the reduction well above its contribution to CO_2 inequality over the period. In this case, its contribution to the reduction was mainly due to the lower coefficients of this variable at the end of the period. That is, it became less relevant in explaining CO_2 emissions from fuel combustion.

As for population aged 16–64, the contribution of this factor to the decrease in the inequality in CO_2 emissions per capita between developing countries is relatively small (much below its share in explaining this inequality). This is due to the persistence of the differences in the variable across developing countries. As regards urbanization, agricultural share and the residual term, their contribution to the reduction of inequality is not much different from their share in explaining this inequality.

4 | CONCLUSION AND POLICY IMPLICATIONS

We have explored the differences in CO_2 emissions per capita between developing countries and how these are influenced by a series of affluence, structural, demographic, and climate variables. For this, we have first performed a regression analysis, contributing to the literature on the determinants of CO_2 emissions with new evidence for the case of developing countries. The results show an N-shaped cubic relationship with GDP per capita, and a significant, though of a moderate magnitude, negative impact on emissions of the agriculture share of GDP and average daily minimum temperatures, while urbanization and particularly the share of potentially active population would significantly increase emissions per capita across countries. An interesting result is that, contrary to similar cross-country studies including developed countries, the industry share of GDP is not a significant determinant of emissions for developing countries, so that pursuing a direct transformation to service economies instead of industrializing their economies would apparently not be associated with lower emissions across developing countries. Other variables such as trade openness, population density or family unit members were discarded from the model used as the basis for our inequality decomposition, as they were found not significant determinants of CO_2 emissions per capita for developing countries.

By using the regression-based inequality decomposition method (Fields, 2003), our analysis indicates the weight of each significant determinant of emissions in explaining the inequality in CO_2 emissions per capita observed between developing countries. It highlighted the principal contribution of economic affluence to these differences (above 30%), which contrasts with the previous only other application of this method to international inequality in CO_2 emissions per capita for a sample including developing and developed countries (Duro et al., 2017), where, despite being quite important, this factor was not the most important contributor to inequality. Actually, our results show clear differences in the relevance of the different factors in explaining the inequality in CO_2 emissions per capita for developing countries than were found in that analysis. The potentially active population factor shows it to be the second main contributor to this inequality (above 20%), though far from the weight found in the cited work. Other factors with different influence are agriculture share, which accounts for a lower part of the inequality between developing countries, and urbanization, which appears to be a more relevant factor in explaining emissions inequality between developing countries than for a mixed sample. This last result is a consequence of the greater impact on emissions shown by the larger coefficient—that is, a greater semi-elasticity—found for this variable in our study on developing countries.

Part of the inequality in CO_2 emissions per capita is explained by climate variables; however, most of the differences are explained by socioeconomic and demographic variables which may be influenced by political changes. Though affluence is the most relevant factor explaining differing emissions between countries, the relationship between emissions and income or production is a complex one, as shown by the cubic relationship found in this study. Hence, it deserves further research to ascertain how, isolating it from the other detected significant factors, some developing countries are able to emit less with the same or even higher level of income per capita than others. The role of technology, which in our study is not properly captured and may be partly hidden in the residual term (and possibly partly in the nonlinear components of affluence), will be of great relevance in the future to allow the development of countries without passing through the most pollution-intensive stages that developed countries and emerging economies have been through (Padilla, 2017). As regards the potentially active population, it is clear that the particular consumption and transport habits related to this demographic group are determining emissions and differences between countries, so that policies should focus on influencing these patterns. Moreover, projections on the age structure of the population may be an informative tool to predict difficulties in controlling CO_2 emissions and even its influence on emissions inequality trends. Urbanization seems to be particularly associated with more pollution-intensive habits in developing countries and in explaining CO_2 emissions per capita differences between them. Developing countries are experiencing a high rate of urbanization that will continue in coming years. Those countries that promote a smart urbanization, avoiding sprawl through smart urban design and, particularly, avoiding locking in carbon-intensive infrastructures will be able to attenuate the impact of urbanization on emissions, while they could gain much by encouraging the potential positive aspects, such as a more efficient energy and land use and easier access to public equipment, infrastructures, markets and information. The more countries succeed on this, the less relevant this factor would become in the future in explaining the inequality in CO_2 emissions. Finally, the search of leap-frogging into a service economy, without passing through industrialization processes, does not seem to be a policy that guarantees lower emissions for developing countries per se, as services are actually associated and complementary to many polluting activities. The processes of specialization may affect emissions differences according to the particular subsectors and regulations that are put into place in order to facilitate development. The impact on emission inequality will also depend on the degree of international specialization, that is, whether countries tend toward greater specialization in different activities or whether there is a tendency to converge to similar production compositions.

Our analysis has provided useful insights for environmental policies for developing countries, which are highly interested in the success of global climate policies that partly depend on their commitments. Knowledge of both the determinants of CO_2 emissions per capita for developing countries as well as on the specific factors that explain the differences between them provide useful information on the variables that lead some developing countries to pollute more or less than others. Moreover, the information obtained is more precise and useful for developing countries than what could be derived from an analysis mixing countries of different development levels, as we have identified significant differences in the relevance of these factors for developing countries. Finally, our analysis has also provided information on the variables whose changes may lead to convergence toward lower emissions levels across developing countries and their relevance in achieving this desired outcome.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ORCID

Emilio Padilla Rosa https://orcid.org/0000-0002-9510-8262

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APPENDIX A

A.1 | RESULTS OF REGRESSIONS INCLUDING NON-SIGNIFICANT VARIABLES

TABLE A1 Cross-country regression on the determinants of CO_2 emissions per capita in developing countries, including industry share of GDP and population density

	1995	2000	2005	2010	2014
Economic affluence					
$GDPpc_i$	0.0045938***	0.0054248***	0.0041544***	0.0026783***	0.0022976***
	(−0.0012373)	(0.0010124)	(0.0008207)	(0.000783)	(0.0006422)
$GDPpc^2_i$	−2.59E−06***	−2.95E−06***	−2.03E−06***	−1.05E−06***	−8.62E−07***
	(−9.63E−07)	(7.31E−07)	(4.90E−07)	(3.93E−07)	(3.04E−07)
$GDPpc^3_i$	4.42E−10**	5.05E−10***	3.07E−10***	1.31E−10**	1.05E−10**
	(2.19E−10)	(1.54E−10)	(8.85E−11)	(5.99E−11)	(4.33E−11)
Economic structure					
$Agriculture\_sh_i$	−0.0177908*	−0.0054323	−0.0098024	−0.0244997**	−0.0205419**
	(0.0095648)	(0.0079245)	(0.0083038)	(0.0101146)	(0.0092152)
$Industry\_sh_i$	0.0053623	0.0061171	0.0029325	−0.0091257	−0.00364
	(0.0093939)	(0.0069932)	(0.0072079)	(0.0075115)	(0.0065966)
Demography					
$Urbanization_i$	0.0112925	0.0052283	0.0166314**	0.0126455**	0.0116814**
	(0.0073531)	(0.0067927)	(0.0063475)	(0.0055119)	(0.0048604)
$Pop\_15\text{-}64_i$	0.1120865***	0.0955881***	0.0883899***	0.0706301***	0.0614523***
	(0.0273812)	(0.0202917)	(0.0176241)	(0.0164901)	(0.0146145)
$Pop\_density_i$	−0.0004135	−0.0000769	−0.0001582	−0.0003454	−0.0004693
	(0.0006476)	(0.000537)	(0.0004912)	(0.0004654)	(0.000394)
Climate					
$tmin_i$	−0.0463598***	−0.0383259***	−0.0192611*	−0.0149795	−0.0276824***
	(0.0118543)	(0.0109674)	(0.0112633)	(0.0118389)	(0.0103326)
Intercept	−1.478362	−1.587155	−1.396747	0.7908071	1.565547
	(1.596097)	(1.13882)	(1.034041)	(0.9964531)	(0.8785616)
N	63	64	66	67	67
F	30.78***	32.14***	35.21***	32.22***	34.48***
R^2	0.8394	0.8427	0.8498	0.8357	0.8448
Adjusted R^2	0.8122	0.8165	0.8257	0.8098	0.8203

Note: Statistical significance is denoted by (*) at the 10% level ($p < .10$); (**) at the 5% level ($p < .05$); and (***) at the 1% level ($p < .01$). Standard errors within parentheses.
Source: Prepared by the authors with World Bank data.

TABLE A2 Cross-country regression on the determinants of CO_2 emissions per capita in developing countries, including average family size

	1995	2000	2005	2010	2014
Economic affluence					
$GDPpc_i$	0.0039704***	0.0048065***	0.0041457***	0.0024568***	0.0020315***
	(0.0013673)	(0.0011625)	(0.0008741)	(0.0008457)	(0.0006807)
$GDPpc^2{}_i$	−2.03E−06*	−2.52E−06***	−2.03E−06***	−9.77E−07**	−7.46E−07**
	(1.03E−06)	(8.47E−07)	(5.48E−07)	(4.48E−07)	(3.40E−07)
$GDPpc^3{}_i$	3.15E−10	4.29E−10**	3.16E−10***	1.30E−10*	9.25E−11*
	(2.32E−10)	(1.81E−10)	(1.03E−10)	(7.16E−11)	(5.00E−11)
Economic structure					
$Agriculture\_sh_i$	−0.0217167**	−0.0096116	−0.0111549	−0.0204713**	−0.0202195**
	(0.010371)	(0.0078925)	(0.0078551)	(0.009471)	(0.0085152)
Demography					
$Urbanization_i$	0.0122971	0.0028862	0.0149189*	0.0134293**	0.0129594**
	(0.0082827)	(0.007874)	(0.0074549)	(0.0061357)	(0.0054115)
$Pop\_15\text{-}64_i$	0.100944***	0.1119065***	0.0990547***	0.0861143***	0.0684715***
	(0.0301279)	(0.0245045)	(0.0203961)	(0.0186352)	(0.0156367)
$Household_i$	−0.0222988	0.0947441	0.0558641	0.1166426	0.074668
	(0.0950194)	(0.0927968)	(0.0784022)	(0.0740466)	(0.0646928)
Climate					
$tmin_i$	−0.054808***	−0.0420796***	−0.0202116	−0.0162542	−0.0295373***
	(0.0121619)	(0.0120469)	(0.012081	(0.0124682)	(0.0107826)
Intercept	−0.3212388	−2.377729	−2.113467	−0.9066825	0.7504471
	(1.962344)	(1.546185)	(1.376608	(1.246411)	(1.077843)
N	55	56	58	60	60
F	31.13***	30.21***	35.36***	33.08***	33.96
R^2	0.8441	0.8372	0.8524	0.8384	0.842
Adjusted R^2	0.817	0.8095	0.8282	0.8131	0.8172

Note: Statistical significance is denoted by (*) at the 10% level ($p < .10$); (**) at the 5% level ($p < .05$); and (***) at the 1% level ($p < .01$). Standard errors within parentheses. $tmin_i$ is almost significant at 10% for year 2005 ($p = .101$).
Source: Prepared by the authors with World Bank data.

TABLE A3 Cross-country regression on the determinants of CO_2 emissions per capita in developing countries, including trade openness

	1995	2000	2005	2010	2014
Economic affluence					
$GDPpc_i$	0.0037119***	0.0050249***	0.0041215***	0.0027686***	0.0023671***
	0.001145	−2.69E−06	0.0007785	0.0007807	0.0006228
$GDPpc^2_i$	−1.98E−06**	4.57E−10***	−2.02E−06***	−1.11E−06***	−8.93E−07***
	8.95E−07	1.53E−10	4.76E−07	3.98E−07	3.04E−07
$GDPpc^3_i$	3.16E−10	4.57E−10***	3.09E−10***	1.43E−10**	1.10E−10**
	2.02E−10	1.53E−10	8.62E−11	6.11E−11	4.38E−11
Economic structure					
$Agriculture\_sh_i$	−0.0166239**	−0.0080251	−0.0080282	−0.0153005	−0.0136497
	0.0079512	0.0069669	0.0075331	0.0092707	0.0081951
$Trade_i$	0.0055248**	0.0004076	0.0010436	0.0005195	0.0009727
	0.0026189	0.0021817	0.0017111	0.0025878	0.0021213
Demography					
$Urbanization_i$	0.0126648**	0.0072037	0.0192472***	0.0162959*	0.015175***
	0.0061968	0.0062956	0.0061576	0.0061336	0.0054625
$Pop\_15\text{-}64_i$	0.1248726***	0.101317***	0.0911194***	0.0685034***	0.0542655***
	0.0223851	0.0180123	0.0151579	0.015126	0.0133868
Climate					
$tmin_i$	−0.0346591***	−0.0380528***	−0.0174526*	−0.0197887*	−0.0344158***
	0.0102016	0.0107291	0.0100845	0.0112401	0.0097276
Intercept	−2.431804*	−1.671822	−1.764719*	0.2868031	1.511569*
	1.40475	1.038934	0.9066277	0.9343298	0.8225286
N	60	64	64	64	65
F	42.38	37.23	43.19	33.78	38.72
R^2	0.8693	0.8441	0.8627	0.8309	0.8469
Adjusted R^2	0.8487	0.8214	0.8427	0.8063	0.825

Note: Statistical significance is denoted by (*) at the 10% level ($p < .10$); (**) at the 5% level ($p < .05$); and (***) at the 1% level ($p < .01$). Standard errors within parentheses. $Agriculture\_sh_i$ is almost significant at 10% for years 2010 and 2014 ($p = .105$ and .101, respectively).
Source: Prepared by the authors with World Bank data.

TABLE A4 Countries included in the estimations shown in the main text

1995	2000	2005	2010	2014
Angola	Angola	Afghanistan	Afghanistan	Afghanistan
Burundi	Burundi	Angola	Angola	Angola
Benin	Benin	Burundi	Burundi	Burundi
Burkina Faso	Burkina Faso	Benin	Benin	Benin
Bangladesh	Bangladesh	Burkina Faso	Burkina Faso	Burkina Faso
Bolivia	Bolivia	Bangladesh	Bangladesh	Bangladesh
Bhutan	Bhutan	Bolivia	Bolivia	Bolivia
Cote d'Ivoire	Cote d'Ivoire	Bhutan	Bhutan	Bhutan
Cameroon	Cameroon	Cote d'Ivoire	Central African Republic	Central African Republic
Congo, Dem. Rep.	Congo, Dem. Rep.	Cameroon	Cote d'Ivoire	Cote d'Ivoire
Congo, Rep.	Congo, Rep.	Congo, Dem. Rep.	Cameroon	Cameroon
Comoros	Comoros	Congo, Rep.	Congo, Dem. Rep.	Congo, Dem. Rep.
Cabo Verde	Cabo Verde	Comoros	Congo, Rep.	Congo, Rep.
Egypt, Arab Rep.	Egypt, Arab Rep.	Cabo Verde	Comoros	Comoros
Eritrea	Eritrea	Egypt, Arab Rep.	Cabo Verde	Cabo Verde
Ethiopia	Ethiopia	Eritrea	Egypt, Arab Rep.	Egypt, Arab Rep.
Ghana	Ghana	Ethiopia	Ethiopia	Ethiopia
Guinea	Guinea	Ghana	Ghana	Ghana
Gambia, The	Gambia, The	Guinea	Guinea	Guinea
Guinea-Bissau	Guinea-Bissau	Gambia, The	Gambia, The	Gambia, The
Honduras	Honduras	Guinea-Bissau	Guinea-Bissau	Guinea-Bissau
Haiti	Haiti	Honduras	Honduras	Honduras
Indonesia	Indonesia	Haiti	Haiti	Haiti
India	India	Indonesia	Indonesia	Indonesia
Kenya	Kenya	India	India	India
Kyrgyz Republic	Kyrgyz Republic	Kenya	Kenya	Kenya
Cambodia	Cambodia	Kyrgyz Republic	Kyrgyz Republic	Kyrgyz Republic
Kiribati	Kiribati	Cambodia	Cambodia	Cambodia
Lao PDR	Lao PDR	Kiribati	Kiribati	Kiribati
Lesotho	Liberia	Lao PDR	Lao PDR	Lao PDR
Morocco	Lesotho	Liberia	Liberia	Liberia
Moldova	Morocco	Lesotho	Lesotho	Lesotho
Madagascar	Moldova	Morocco	Morocco	Morocco
Mali	Madagascar	Moldova	Moldova	Moldova
Mongolia	Mali	Madagascar	Madagascar	Madagascar
Mozambique	Myanmar	Mali	Mali	Mali
Mauritania	Mongolia	Myanmar	Myanmar	Myanmar
Malawi	Mozambique	Mongolia	Mongolia	Mongolia
Niger	Mauritania	Mozambique	Mozambique	Mozambique
Nigeria	Malawi	Mauritania	Mauritania	Mauritania
Nicaragua	Niger	Malawi	Malawi	Malawi
Nepal	Nigeria	Niger	Niger	Niger
Pakistan	Nicaragua	Nigeria	Nigeria	Nigeria
Philippines	Nepal	Nicaragua	Nicaragua	Nicaragua
Papua New Guinea	Pakistan	Nepal	Nepal	Nepal
Rwanda	Philippines	Pakistan	Pakistan	Pakistan

TABLE A4 (Continued)

1995	2000	2005	2010	2014
Sudan	Papua New Guinea	Philippines	Philippines	Philippines
Senegal	Rwanda	Rwanda	Papua New Guinea	Papua New Guinea
Solomon Islands	Sudan	Sudan	Rwanda	Rwanda
Sierra Leone	Senegal	Senegal	Sudan	Sudan
El Salvador	Solomon Islands	Solomon Islands	Senegal	Senegal
Eswatini	Sierra Leone	Sierra Leone	Sierra Leone	Sierra Leone
Chad	El Salvador	El Salvador	El Salvador	El Salvador
Togo	Eswatini	Sao Tome and Principe	Sao Tome and Principe	Sao Tome and Principe
Tajikistan	Chad	Eswatini	Eswatini	Eswatini
Tunisia	Togo	Chad	Chad	Chad
Tanzania	Tajikistan	Togo	Togo	Togo
Uganda	Tunisia	Tajikistan	Tajikistan	Tajikistan
Ukraine	Tanzania	Tunisia	Tunisia	Tunisia
Uzbekistan	Uganda	Tanzania	Tanzania	Tanzania
Vietnam	Ukraine	Uganda	Uganda	Uganda
Vanuatu	Uzbekistan	Ukraine	Ukraine	Ukraine
Yemen, Rep.	Vietnam	Uzbekistan	Uzbekistan	Uzbekistan
Zambia	Vanuatu	Vietnam	Vietnam	Vietnam
Zimbabwe	Yemen, Rep.	Vanuatu	Vanuatu	Vanuatu
	Zambia	Yemen, Rep.	Yemen, Rep.	Yemen, Rep.
	Zimbabwe	Zambia	Zambia	Zambia
		Zimbabwe	Zimbabwe	Zimbabwe