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# The causal factors of international inequality in $CO_2$ emissions per capita: A regression-based inequality decomposition analysis

**Abstract**

This paper uses the possibilities provided by the regression-based inequality decomposition (Fields, 2003) to explore the contribution of different explanatory factors to international inequality in $CO_2$ emissions per capita. In contrast to previous emissions inequality decompositions, which were based on identity relationships, this methodology does not impose any a priori specific relationship. Thus, it allows an assessment of the contribution to inequality of different relevant variables. In short, the paper appraises the relative contributions of affluence, sectoral composition, demographic factors and climate. The analysis is applied to selected years of the period 1993–2007. The results show the important (though decreasing) share of the contribution of demographic factors, as well as a significant contribution of affluence and sectoral composition.

**JEL codes**: C19; D39; Q43.

**Keywords:** $CO_2$ emissions, international emissions inequality, regression-based decomposition.

## 1. Introduction

There is a huge inequality in the international distribution of $CO_2$ emissions. Differences in emissions per capita and in their determinants lead to different views on the appropriate criteria to distribute abatement efforts among countries—and even on the ambition of mitigation goals—and so hamper mitigation agreements. The design of policies should appropriately take into account these inequalities, which show different responsibilities for the problem, as well as the different drivers of them. A wider participation in international abatement agreements on the part of developing and emerging economies would be facilitated by the perceived fairness of abatement sharing. This perceived fairness will increase if countries with greater responsibility in the problem are charged with the most important part of mitigation efforts. An agreement assuming a very uneven distribution of the $CO_2$ absorption capacity of the atmosphere and not involving strong efforts by the main countries responsible for causing the problem would tend to disincentivise the participation of developing countries. These countries claim that the global sink capacity is being disproportionally used by the inhabitants of richer countries, which are also responsible for past overuse leading to the intensification of the greenhouse effect. On the other hand, the greater the degree of inequality, the more reluctant the main emitters may be to participate in agreements asking them to assume most of the burden of emissions reduction.

Disparities in emissions per capita are due to factors that follow different paths in different countries. A good knowledge both of inequality changes and of the drivers of the differences in emissions per capita and their trajectories over time is essential to inform the debates on policy design and on the criteria to distribute abatement efforts.

The conclusions both for analysing the feasibility of agreements of a given situation and for informing policy design would be quite different depending on the different contributions of the relevant factors to emissions inequality.

The increase in papers in recent years dealing with the international distribution of $CO_2$ emissions is noticeable. These analyses have followed two complementary paths. First, several works employ the methodologies developed in the literature on the measurement of income inequality (some of the reference works include Atkinson, 1970; Sen, 1973; and Cowell, 2011). They focus on aspects such as the properties of the measurements and their factorial decomposition. The application and adaptation of this literature to the analysis of environmental indicators extend the analysis made in the field of income distribution. Some references in this line include Heil and Wodon (1997, 2000), Alcántara and Duro (2004), Hedenus and Azar (2005), Duro and Padilla (2006), Padilla and Serrano (2006), Cantore and Padilla (2010), Cantore (2011) and Duro (2012). Second, there are some works analysing the international distribution of $CO_2$ (and other environmental indicators), but by means of the methods developed in the literature on economic growth and convergence (Barro and Sala i Martín, 1991; Quah, 1995). Some examples of these works are Strazicich and List (2003), Nguyen Van (2005), Aldy (2006), Ezcurra (2007), Romero-Ávila (2008), Criado and Grether (2010), Jobert et al. (2010) and Barassi et al. (2011). Both lines of research analyse similar issues with different tools and coincide in the relevance of measuring emissions disparities as a tool for helping policy design.

Such proliferation of analyses of the international distribution of $CO_2$ per capita might be seen as the result of the awareness of ecological limits as well as of the need to inform discussions on the different responsibilities and on the mitigation efforts to be assumed by different countries. Moreover, this research complements the abundant literature focused on the study of the driving forces of $CO_2$ emissions (Grossman, 1993; Stern et al., 1996; Suri and Chapman, 1998; Torras and Boyce, 1998; York et al., 2003; Sharma, 2011). Among them, affluence, population, technology (the factors of the so-called IPAT identity proposed by Ehrlich and Holdren, 1971),[1] economic structure, demographic characteristics and climate characteristics are usually considered among the main drivers of environmental impacts. These analyses usually consist of econometric models whose emphasis is on the regression coefficients and their significance. However, as far as we know, the contribution of these factors to emissions inequality measures has not yet been explicitly and precisely approached. In this sense, a relevant methodological basis to approach such analysis is the regression-based inequality decomposition approach (RBID hereafter), which allows the development of such analysis without being constrained to an automatic accounting relationship between explanatory factors and emissions. Actually, previous analyses decomposing emissions per capita inequality have taken as reference multiplicative identities and group decompositions (Duro and Padilla, 2006). In contrast, the RBID technique allows one to widen the list of explanatory factors unrestrictedly.

The method proposed in this paper consists of, first, running an auxiliary econometric estimation to derive an additive decomposition of $CO_2$ emissions per capita. The model we will employ as reference for the identification of determinant factors may be seen as an extended version of the econometric models usually employed to test the environmental Kuznets curve hypothesis or the STIRPAT models. In short, it includes as explanatory factors affluence, demographic factors, sectoral composition and a climate variable. Second, the model applies the methods of additive decomposition of inequality (Shorrocks, 1982, 1983) to determine factoral contributions. Therefore, from a methodological point of view, the proposed technique merges two hot research topics:

the analysis of inequalities in the contribution to climate change and the econometric estimation of environmental impact driving forces. The contribution of such factors to global emissions inequality depends on two basic parameters: the average direct relationship between the examined factor and countries' $CO_2$ per capita (i.e. coefficient-effect), and the relative magnitude of the international variation of the factor (i.e. dispersion effect). The methodology is applied to the analysis of international inequality in $CO_2$ emissions per capita for the period 1993–2007.

Our analysis will contribute, first, to informing how the evolution of disparities leads or does not lead to a situation in which it is more likely that countries share interests and perceptions of how to distribute abatement efforts; second, it will contribute to the analysis of the determinants of emissions and how they change over time; and third, it will show the factors behind the trajectory of inequality. These factors should be adequately taken into account for a proper design of policies that facilitate wider and fairer agreements.

The remainder of this paper is organised as follows. Section 2 describes the RBID methodology. Section 3 measures the international inequality in $CO_2$ emissions per capita and presents the results of the estimation of the driving forces of emissions and their contribution to the international inequality of $CO_2$ emissions per capita according to the proposed methodology. Section 4 concludes the paper.

## 2. The regression-based inequality decomposition: methodological aspects

Inequality decomposition methods allow researchers to quantify which part of total inequality is attributable to different components. The traditional additive decomposition approach (Shorrocks, 1982) consists in breaking down the inequality of any variable according to its additive components. Additionally, such an approach has been extended to decomposition into multiplicative factors by taking advantage of logarithmic inequality measures such as the Theil index. These methods require a consistent identity in order to perform the decomposition.[2] Therefore, the main restriction is that the contributions to inequality considered are limited to the components of the mathematical identity.

In contrast, the RBID approach allows us not only to account for the contribution to inequality of different components, but also to undertake causal analysis (since the contributions to inequality are attributed to the explanatory variables of an econometric model). Therefore, the model can incorporate any significant explanatory variable contributing to $CO_2$ emissions inequality.[3] The first step is to construct a linear regression function such as the ones typically used to estimate the driving forces elasticities for a given environmental pressure (*E*):

$$E = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_K X_K + \varepsilon \tag{1}$$

Where $E$ is the vector of the environmental pressure in the different countries considered and $X_i$ (i=0,…,K) the vectors for the driving forces or determinants of this pressure.

Expression (1) presents environmental pressure, in our case $CO_2$ emissions per capita, as the sum of $K$ explanatory variables plus the constant and error terms. So, we can rearrange it and obtain:

$$E = \sum_{k=0}^{K+2} \beta_k X_k \tag{2}$$

The RBID is based on considering the product of the estimated coefficient $\beta_k$ and its variable $X_k$ as the "causal component" of $CO_2$ emissions per capita, where the coefficient plays the role of weighting the importance of component *k*. The explanatory variables jointly with the constant and the residual form a consistent identity as those required by traditional decomposition methods, so that the natural decomposition rule can be performed by sources (see Shorrocks, 1982; Fields, 2003).

Although there are other methods to decompose inequality using regression-based techniques, we use the Fields (2003) method because of its simplicity and analogy to natural source decomposition described.[4] In this RBID approach the functional form of the model is restricted to a semi-log linear function:[5]

$$\ln E = \sum_{k=0}^{K+2} \beta_k X_k \tag{3}$$

Once the semi-log model is estimated, the procedure continues by taking variances on both sides of the equation. Note that the variance of the logarithm of emissions per capita is a common inequality index (see Cowell, 2011):

$$\operatorname{var}(\ln E) = \operatorname{var}\left( \sum_{k=0}^{K+2} \beta_k X_k \right) \tag{4}$$

By rearranging the right hand side of expression (4), we obtain the variance of logarithms as a sum of the covariances between each causal component and the dependent variable (the logarithm of $CO_2$ emissions per capita):

$$\mathrm{var}(\ln E) = \sum_{k=0}^{K+2} \mathrm{cov}(\beta_k X_k, \ln E) \qquad (5)$$

This result is highly convenient since in the inequality literature those covariances are the natural decomposition of the variance, which indeed is a consistent decomposition rule. Hence, in order to obtain the relative contribution of each causal component, we define:

$$s_k(\ln E) = \frac{\mathrm{cov}[\beta_k X_k, \ln E]}{\mathrm{var}(\ln E)} \qquad (6)$$

being $s_k$ the percentage contribution of factor $k$ to the level of inequality observed.[6]

Since the coefficients of the regression play a weighting role, it may be interesting to know whether the different trajectories of $s_k$ are caused by changes in the dispersion of factor $k$, or by changes in its importance in the function measured by $\beta$:

$$s_{kt} - s_{kt-1} = \frac{\mathrm{cov}(Z_t^k, \ln E_t)}{\mathrm{var}(\ln E_t)} - \frac{\mathrm{cov}(Z_{t-1}^k, \ln E_{t-1})}{\mathrm{var}(\ln E_{t-1})} =$$
$$\left[\frac{\mathrm{cov}(\hat{Z}_{t-1}^k, \ln E_t)}{\mathrm{var}(\ln E_t)} - \frac{\mathrm{cov}(Z_{t-1}^k, \ln E_{t-1})}{\mathrm{var}(\ln E_{t-1})}\right] + \left[\frac{\mathrm{cov}(Z_t^k, \ln E_t)}{\mathrm{var}(\ln E_t)} - \frac{\mathrm{cov}(\hat{Z}_{t-1}^k, \ln E_t)}{\mathrm{var}(\ln E_t)}\right] \qquad (7)$$

where $Z_t^k = \beta_{kt} X_{kt}$ and $\hat{Z}_{t-1}^k = \beta_{kt-1} X_{kt}$. The first term of the right-hand side is the *dispersion effect* since the coefficients are not allowed to vary (and so only the dispersion changes between *t - 1* and *t*). The second term is the *coefficient effect* since the dispersion of vector $X_k$ is not allowed to vary (so only the coefficient changes between both periods).

Additionally, we may be interested in knowing the contribution of factor *k* to the change in inequality level between two periods. That inequality change contribution is expressed as:

$$\delta_k \equiv \frac{s_{kt} I(.)_t - s_{kt-1} I(.)_{t-1}}{I(.)_t - I(.)_{t-1}} \tag{8}$$

where I(.) is the inequality measure for period t. Notice that expression (8) is not restricted to the use of any particular inequality index. Our choice for the empirical analysis will be neutral indexes such as the generalized entropy index (GE(2)) or the coefficient of variation (CV), like in Duro (2012).[7]

## 3. International inequality in $CO_2$ emissions per capita and explanatory factors

As stated above, we use logarithmic variance as a reference index. This choice is associated to the RBID methodology used, which, based on the work of Fields (2003), uses this measure for consistency. In any case, as shown below, the factoral decomposition can be applied to any consistent inequality index. Logarithmic variance is a well-known measure that fulfils the scale-independent property (that is, is a relative measure) but does not fulfil the progressivity principle for high observations, which does not have a significant impact in our case (Cowell, 2011).

Our analysis covers the period from 1993 to 2007 by eight biannual cross-section samples. The data used for each year cover at least 92% of world $CO_2$ emissions, 95% of world population and 96% of world GDP. Although the samples may be different among years, the results are virtually equivalent with balanced data. This means the results with balanced data (all years with the same countries) do not show any significant differences with the results obtained with the non-balanced sample (where we take the maximum number of countries in each sample). This is because the countries that are not included in a specific sample represent a very little proportion of the world $CO_2$ emissions (and of the world population and GDP). The data used comes from the World Bank (2013).

Figure 1 shows the international dispersion of $CO_2$ emissions per capita for the period 1993–2007. Initially, it can be noted that in this period the total emissions increased 40% and the per capita emissions 16.7%. Coinciding with this increase was a significant reduction in dispersion, with three different subperiods. In the first, from 1993–1997, there was an important reduction of inequality; in the second, 1997–2003, there was a stabilisation of inequality; and finally, in the third, 2003–2007, there was a new important reduction. Therefore, we may say that the international responsibility in $CO_2$ emissions, at least in per capita terms, is becoming more diffused.

[FIGURE 1 ABOUT HERE]

However, underlying such a trend different stories may be occurring. Are the major polluters reducing their emissions per capita, or, in contrast, are the minor polluters increasing their emissions? Or may it be both things? Observing the quantiles distribution in Table 1, the latter appears as more plausible since the first percentile per capita emissions increased 64%, while percentile 0.9 increased only 5%. Therefore, from the environmental point of view this reduction in inequality cannot be identified as good news as it was based on a greater increase in lower emitters and not on a reduction in major emitters. Obviously, in the quantiles analysis there is the anonymity axiom, i.e. we may talk of different countries for the same quantiles in different years.

[TABLE 1 ABOUT HERE]

Decomposing the inequality in $CO_2$ emissions per capita according to its determinants will enlighten the analysis of the causes of this inequality, complementing previous accounting approaches. The dependent variable used in the model is the $CO_2$ emissions per capita of the different countries in log scale, while the independent variables are those typically used in the literature (such as in the above cited STIRPAT models and the extended models used to test the environmental Kuznets curve). Table 2 details the descriptive statistics of the variables used in the model.

[TABLE 2 ABOUT HERE]

The results obtained when applying the RBID methodology are twofold. First, we obtain the regression results of the estimation of the determinants of $CO_2$ emissions per capita. Second, using the regression results we estimate the contributions of the explanatory variables to the international inequality in $CO_2$ emissions per capita by using expression (6) of the previous section. The OLS results (i.e. auxiliary regressions) are presented in Table 3. The model estimated explains close to 85% of the cross-country log-variance in $CO_2$ emissions per capita (except for 1993, in which it explains around 80%), indicating that used variables provide a good fit. The significance and the sign of the coefficients obtained are coherent with the empirical literature dealing with the determinants of $CO_2$ emissions. Besides, this high significance points out that multicollinearity may not be a very important problem. Indeed, we calculated quadratic partial correlations between the exogenous variables and the dependent variable, and the low values obtained indicate that multicollinearlity is not a substantial problem in our estimation.[8]

Since it is a semi-log model, we must interpret the significant coefficients as semi-elasticities, i.e. an increase (decrease) of one unit in the explanatory variable yields a $\beta$% increase (decrease) in the dependent variable. Hence, focusing on 2007 coefficients, an increase in one dollar of GDP per capita yields a 0.01% increase of $CO_2$ emissions per capita, while an increase in the climate normal minimum temperature would yield a -2.10% decrease in emissions per capita, and so on.

We are estimating cross-country determinants and so are not making assumptions about the individual behaviour of countries over time. A wrong assumption often made in the environmental Kuznets curve literature, when making panel data estimations, is to assume the same functional form and parameters for each country in their relationship between income (and other variables) and environmental pressure (or impact) over time. This assumption has been clearly rejected when appropriately tested (see Perman and Stern, 1999 and 2003; List and Gallet, 1999; Dijkgraaf and Vollenberg, 2005; Martínez-Zarzoso and Bengochea-Morancho, 2003 and 2004; Piaggio and Padilla, 2012). Thus, our results just show cross-country relationships between independent variables that change across countries and $CO_2$ emissions per capita in a given moment of time. These relationships may be caused by different underlying reasons (levels of development, international specialisation, different regulations, etc.) and be the result of different patterns followed by different countries, as the literature seems to support.

Affluence variables indicate the existence of a non-monotonic relationship since both quadratic and cubic GDP per capita variables are significant. This shows an N-shape cross-country pattern (Friedl and Getzner, 2003; Sengupta, 1996; Taskin and Zaim, 2000), though with a basic increasing segment and small coefficients for quadratic and cubic terms, and so the environmental Kuznets curve hypothesis is not supported by the data. Therefore, it may be stated that in most cases greater affluence is accompanied by greater $CO_2$ emissions per capita.

Attending to sectoral composition determinants, a priori, a greater weight of industrial sectors is expected to be associated with greater emissions, while those economies with greater weight of services, and specifically of knowledge-based technology-intensive industries, are expected to have lower emissions than those based on energy intensive industry (Dinda, 2004). In any case, it should be taken into account that several services also make an intensive use of energy (Suh, 2006; Alcántara and Padilla, 2009), and the idea that services are immaterial sectors should be dismissed. Sectoral composition coefficients—industrial GDP share and agricultural GDP share—show the expected values. A positive coefficient of industrial share must be interpreted as the $CO_2$ emissions percentage increase when the share of the sector increases 1% and the base sector (services) decreases in this same percentage. In contrast, the agricultural share coefficient shows the inverse relationship with $CO_2$ emissions per capita.

Demographic variables have positive significant coefficients, indicating their influence in spurring emissions per capita. The non-dependent population (aged 15–65), which captures the most consumerist and productive segment of the population, exhibits an important role in driving emissions: a 1% increase represents a cross-country increase of 8–10% in $CO_2$ emissions per capita. This suggests that population age structure may play a significant role in explaining differences in emissions. This contrasts with previous results in the literature, such as Dietz et al. (2003) for the case of the ecological footprint and Cole and Neumayer (2004) for the case of total $CO_2$ emissions, who did not find significant coefficients for age distribution. Some differences with the study of

Cole and Neumayer (2004) that may explain the different result is the use of per capita instead of total emissions, as well as the set of variables included our model.

Urban population share exhibits a lower effect but is still significant and positive, except for years 2001 and 2007 when the estimated coefficient is not significant. Our estimates are consistent with the previous evidence in the literature (see Parikh and Shukla, 1995, for the evidence on developing countries; and Cole and Neumayer, 2004, for an international cross-section sample including developing and developed countries). We find, however, that the coefficient decreases over time. The positive impact of urbanisation on emissions stems from the fact that an urban lifestyle and facilities lead people to consume more energy and thus generate more $CO_2$ emissions in urban areas than in rural ones, especially in developing countries, which represent the biggest part of the world. The migration of rural workers to urban areas in search of better jobs tends to yield a sprawl growth of cities with large suburbs and the need to commute every day by private vehicle. There is also more use of fossil fuels instead of fuel wood and longer distances travelled for the provision of food and other products (Jones, 1989; Parikh and Shukla, 1995). Moreover, the use of public and private motor vehicles—cars, buses, and motorcycles—is likely to be more extended in urban than in rural areas (Cole and Neumayer, 2003). However, the impacts of urbanisation on emissions are of a different type, and although most studies indicate that urbanisation tends to increase energy consumption and emissions due to the abovementioned reasons, there are other impacts that may go in the opposite way as urbanisation may be accompanied by greater access to information, technical innovation and efficient land and energy use, which may contribute to the reduction of energy consumption and emissions in the long run (Jiang et al., 2008; Jiang and Hardee, 2011). Actually, there are mixed results on the impact of urbanisation on energy consumption and emissions

(Jiang and Hardee, 2011). The decreasing coefficient of the variable may indicate that some of the gains associated with urbanisation may now be more effectively compensating the negative effects.

Both demographic variables, jointly with others like household size (Liu et al., 2003) have only been studied to a limited extent in the literature but are projected to have quite an important impact on the future evolution of emissions (Jiang and Hardee, 2011).

Lastly, the climate control variable, proxied by the climate normal[9] of minimum temperature, indicates that an increase in normal temperatures of 1 °C would decrease $CO_2$ emissions per capita approximately by 2%. This result shows the fact that colder climates require greater amounts of energy for heating and lower for cooling, the first impact being more important. Previous studies, such as Neumayer (2004), also found that a cold climate is significantly associated with greater $CO_2$ emissions.

[TABLE 3 ABOUT HERE]

The regression results are used to calculate each factor's weight, which jointly with variable's vector dispersion (its inequality) will yield the contributions to per capita $CO_2$ emissions inequality observed. Table 4 presents the relative factor contributions to inequality (expression 6).

[TABLE 4 ABOUT HERE]

The affluence factor—which groups the GDP per capita variables—increased its contribution significantly to emissions inequality, reaching its largest share in 2007 with 21%.[10] Table 5 decomposes the change in this relative contribution of each factor into the two basic elements explaining it according to equation (7). Thus, these changes could be explained by a dispersion-effect—and so by changes in the weight of the international variability of the factor—, by changes in the direct relationship between the factor and $CO_2$ emissions per capita according to auxiliary regressions (Table 3), or by both. Taking the whole period, in which the relative contribution of this factor to the international inequality in $CO_2$ emissions per capita increases by 6.5%, the result is explained by the relative increase in the dispersion component of this variable.

Sectoral factors contribute 24.4% to total inequalities in 2007, ranging between 19.7% in 1993 to 30.9% in 1997. In any case, the two factors change in different directions: there is a significant decrease in the importance of the industrial share and a relevant increase in the role of the agricultural share. While in 1993 the agricultural GDP share made a lower contribution than the industrial one, both contributions being of similar weight (8.9% and 10.9%, respectively), the relative relevance of both factors reverse, and for the last year considered the contribution to inequality of the agricultural share is more than four times the one of the industrial share (19.8% and 4.6%, respectively). It is remarkable that the increase in the importance of the agricultural share to explain $CO_2$ emissions differences, which is concentrated in the period 1993–1997, is mainly given by a coefficient effect (Table 5). Thus, its explanatory power in the regression increased significantly while its coefficient became more negative. That is, a greater share of agriculture—and so lower of services—is increasingly associated with lower relative emissions. This different sectoral structure has increased its relative contribution to emissions inequality, given the small importance of the dispersion component. This may be seen as support for the rejection of the notion of service economies as immaterial economies, as the service sector includes activities which require great use of energy, both directly—such as transport services—as well as indirectly—such as hotels and restaurants (Suh, 2006; Nansai et al., 2007; Alcántara and Padilla, 2009; Fourcroy et al., 2012; Piaggio et al., 2015). Moreover, some of these high-polluting service activities have experienced an important development in the last decades.

According to our results, demographic characteristics play the most important role in explaining inequality in $CO_2$ emissions per capita, accounting for 34% of it. In the first years of the sample the urbanisation variable contributed as much to inequality as the non-dependent population variable, 17.4% and 22.3%, respectively. Nonetheless, the relative contribution of urbanisation reduced its level to a much lower value (3.2%). In contrast, non-dependent population increased its relative contribution over the period. In 2007 it explains 30% of international inequality in $CO_2$ emissions per capita. The reduction in the relative contribution of the urbanisation variable, which mainly occurred between 1993 and 1997, is largely attributable to the coefficient effect. As shown in Table 3, the positive relationship between urbanisation and greater $CO_2$ per capita decreases until being non-significantly different from zero in 2007. The decreasing importance in explaining global inequality—jointly with an important reduction in inequality levels—means that some of the abovementioned gains associated with urbanisation may now be more effectively compensating the dominant negative effects.

In contrast, the relative contribution of the age structure of population has increased, and the share of non-dependent population becomes the main explanatory factor of inequality. In this case, both parameters have contributed to this relative change, both the dispersion component (relative increase in the international dispersion in this variable) and the coefficient effect, for the clear increase in the relationship between non-dependent population share and emissions per capita, which increases from 0.078 to 0.089. The increase in the dispersion effect is due to the stability in the international dispersion of this variable in front of the decrease in the dispersion of the logarithm of emissions per capita. As regards the intensification of $CO_2$ emissions associated to non-dependent population, it seems clear that its greater mobility and energy intensive consumption holds over time as a driver explaining differences between countries.

The contribution of climate variable is quite stable over time, and explains only 5% of the differences in $CO_2$ emissions per capita. A direct conclusion is that international differences in $CO_2$ emissions per capita are mainly caused by anthropogenic $CO_2$ drivers.

Last, the residual contribution, which plays a significant role, needs a previous comment. In the typical applications of the STIRPAT models, T of Technology is estimated in the residual term rather than separately (see York et al., 2003). Therefore, we may interpret that the residual could show in part a technological effect where the resources are more efficiently used, though it may also be showing the impact of other omitted variables. Consequently, international spillovers may be occurring in benefit of more equitable per capita emissions. Such greater efficiency may be spurred on by either private gains in resource saving or environmental policy regulations. The contribution of this residual to total inequality in $CO_2$ emissions per capita was quite stable, around 15% after its decline in first years.

[TABLE 5 ABOUT HERE]

Once we know the different relative contribution of factors to $CO_2$ inequality, it is interesting to analyse the contribution of those factors to inequality change over the period analysed (expression 8 above). As we saw in Figure 1, the inequality between countries in $CO_2$ emissions per capita decrease in the period considered. Other studies also point in the same direction (Heil and Wodon, 2000; Duro and Padilla, 2006; Padilla and Serrano, 2006). In our period, the reduction in inequality measured with log-variance was -18%. Table 6 presents the relative contribution of each factor to such inequality change. Those factors that are presented with a negative contribution change are the factors that have contributed to making the distribution of emissions more unequal. In contrast, those factors with a positive sign have contributed to a lower inequality in $CO_2$ emissions per capita. The main driver of the reduction in emissions inequality was urbanisation, which accounts for 82.1% of the whole reduction. The industrial share and the residual—which may partly show a technology effect—also made a significant contribution to the reduction of $CO_2$ inequality, with 39.7% and 42.8%, respectively. In contrast, we could say that $CO_2$ inequality could have decreased even more if affluence, agricultural share or non-dependent population had contributed in an opposite direction of what they did.

[TABLE 6 ABOUT HERE]

## 4. Conclusions

This paper contributes to the literature of the international distribution of environmental pressures and especially to the literature focused on the empirical measurement of the international inequality of $CO_2$ emissions. The analysis of the international distribution of $CO_2$ emissions per capita is of great relevance to inform the debates on climate change responsibilities, the design of future agreements and the international distribution of abatement efforts.

We have used causal components instead of the usual analytical (identity) components examined in the literature of the measurement of environmental indicators inequality. The estimation of a model of the determinants of $CO_2$ emissions per capita has enabled us to decompose the international inequality in these emissions in terms of affluence, productive structure, demographic characteristics and a climate variable showing differences in average daily minimum temperatures (variables that have often been used in STIRPAT models, and in the models employed to test the environmental Kuznets curve hypothesis, among others). We have used the RBID methodology developed by Fields (2003) which, despite being widely applied in empirical studies of income inequality, has not yet been applied to carbon emissions as far as we know. The empirical application of such a method opens the door to new possibilities in the research of distributional issues of the environment–society relationship.

The empirical results contribute significantly to expanding knowledge of the factors contributing to the international disparities of $CO_2$ emissions per capita. As may be expected, 95% of such disparities are accounted for by anthropogenic driving forces (since climate control contributed only around 5%). The country's affluence factor was found as a variable contributing significantly to inequality, which means that remaining differences in GDP per capita are still avoiding greater reductions in emissions inequality. According to our results, its relative contribution, despite having increased to 20%, is not the main driving force explaining emissions per capita differences. As for demographic variables, population age distribution (measured by non-dependent population share) appears as the main contributor to the analysed inequality because of its importance in spurring $CO_2$ emissions per capita rather than by its dispersion among countries. This factor contributed to increasing inequality of emissions per capita during the period analysed. In contrast, of the factors considered, urbanisation became the lowest contributor to international disparities in $CO_2$ emissions. The reason must be found in its lower importance in explaining emissions (coefficient effect) rather than in its dispersion. Finally, the role played by the residual may (with caution) be seen partly as the consequence of international technology spillovers, since it has contributed to narrow differences between countries in terms of emissions per capita.

The unequal use of the global sink capacity of the Earth is closely related to the difficulty of reaching consensus on how to share the burden of emissions mitigation and so appears as one of the main barriers to achieving effective international agreements on emissions control and mitigation. Moreover, the design of agreements could not be done without appropriately taking into account this unequal contribution to the problem and the reasons leading to it, if wide participation is to be achieved. The present paper provides information on the main factors behind the international inequalities in emissions per capita and so, the research indicates some of the roots of the difficulties of achieving global mitigation agreements. Besides, it gives some clues to which factors could lead to a greater convergence or divergence of emissions per capita among countries over time. According to our results, some implications could be highlighted. First, it seems of great relevance to analyse the different consumption patterns associated with demographic factors and how they can change over time. Analysing in depth the different energy consumption and $CO_2$ emissions patterns associated to urbanisation and to the share of potentially active population seems of great importance to understanding emissions drivers, differences across countries and how can they change over time. These results also indicate the need to focus policies on controlling the emissions associated with these patterns. Second, the objective of economic convergence, which is a highly desirable objective by itself, would have a clear impact on reducing emissions inequality and so facilitating agreements between countries.

Third, the change in emissions inequality associated with different sectoral compositions may depend on whether future economies tend toward convergence to more similar economic structures or whether the trend is to increase international specialisation. In any case our results show that those countries more specialised in services tend to increase their differences in emissions with those specialised in agriculture, in contrast with the often-popular idea that the tertiary sector is a cleaner sector. Finally, though the residuals of our estimation may be the result of different things, they may be indicating that one of the ways in which more is to be gained is to decrease emissions differences via more effective technological diffusion.

## Notes

[1] York et al. (2003) turned that accounting equation into a stochastic regression model, allowing them to make a test hypothesis and also to introduce further determinants of the environmental impact.

[2] These analytical decomposition methods have been applied to ecological footprint in White (2007), Teixido-Figueras and Duro (2012) and Duro and Teixidó-Figueras (2012). For the case of $CO_2$ emissions, Duro and Padilla (2006) made a multiplicative decomposition of the contribution of Kaya (1989) factors.

[3] Most RBID applications analyse income inequality from a micro-approach, so there is an income-generating function, and income inequality is decomposed in terms of the typical explanatory variables of those models: race, education level, gender, age, etc. (e.g. Cowell and Fiorio, 2009; Fields, 2003; Gunatilaka and Chotikapanich, 2009; Morduch and Sicular, 2002; Wan, 2004).

[4] There are several empirical applications to income inequality comparing results obtained according to the different methods of RBID. Very often they conclude that there are no significant differences (Cowell and Fiorio, 2009; Fields, 2003; Gunatilaka and Chotikapanich, 2009; Morduch and Sicular, 2002; Wan, 2004).

[5] The semi-log model $Ln(E) = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + ... + \beta_k F_k + \varepsilon_i$ is equivalent to $E = \exp(\beta_0 + \beta_1 F_1 + \beta_2 F_2 + ... + \beta_k F_k + \varepsilon_i) = \exp(\beta_0) \cdot \prod_{k=1}^{k} \exp(\beta_k F_k) \cdot \exp(\varepsilon_i)$. Then, the contribution $\beta_0$ is null since it is a constant to each observation.

[6] Independently of the index chosen by the researcher to assess inequality, the natural decomposition of the variance is the unique unambiguous rule given that it is the only decomposition rule that allocates indirect effects among components in a non-arbitrary way. In other words, the contribution of factor k is independent of the inequality index used (see Cowell, 2000; Shorrocks, 1982, 1983).

[7] GE(2) corresponds to the Theil index with the sensitivity parameter equal to 2. It can be expressed as a linear transformation of CV. The CV is in fact a statistical dispersion index which is scale invariant and that considers all observations uniformly, regardless of its position in the distributive ranking (Duro, 2012).

[8] As can be expected the higher correlations belong to cubic and quadratic terms of GDP per capita; however, it must be taken into account that the non-collinearity assumption is about linear relationships among regressors, and despite its high correlation with linear GDP per capita, the cubic and quadratic

terms are a non-linear relationship. Hence, it does not violate the basic assumption (Gujarati and Porter, 2009). Nevertheless, the results suggest that a non-linear relationship between GDP and $CO_2$ fits better, although the linear term is clearly predominant. Regarding the rest of the explanatory factors, their Variation Inflation Factors (VIF) are well within accepted standards. As a robustness check, other models have been estimated with different regressors than those in Table 3. Results obtained were virtually equivalent.

[9] Climatologists define a climatic normal as the arithmetic average of a climate element (such as temperature) over a prescribed 30-year interval in order to filter out many of the short-term fluctuations and other anomalies that are not truly representational of the real climate. The last climatic normal available is for the period 1971–2000.

[10] This weight is clearly lower than the obtained by Duro and Padilla (2006) with a different methodology. Their study decomposed per capita $CO_2$ emissions inequality by a multiplicative identity (Kaya factors) using the Theil index. As a result, they obtained an affluence net contribution close to 60%, being the main contributor to $CO_2$ inequality. However, this difference can be explained by some methodological factors. First, the Kaya identity used in Duro and Padilla (2006) assumes elasticity proportionality by construction, while in our regression model the elasticities are allowed to vary among factors (see York et al., 2003). Second, the affluence contribution is more precisely defined and isolated in our paper, given the more detailed list of potential factors. Their study can therefore be gathering effects that in our case are separated, such as the ones associated with demographic and structure factors.

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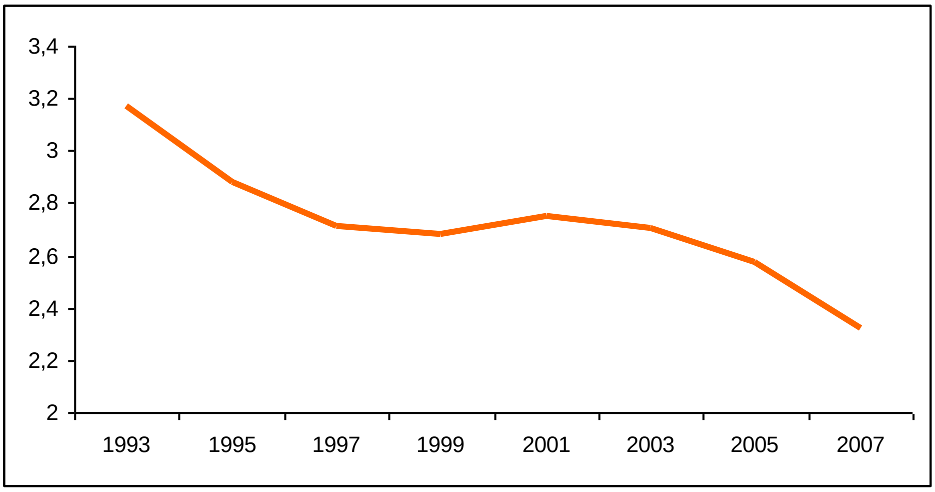
## FIGURES

**Figure 1. International inequality in $CO_2$ emissions per capita measured by log-variance**




Source: Produced by the authors based on World Bank (2013).

## TABLES

### Table 1. Distribution of countries (by quantiles) and changes in carbon emissions per capita, 1993–2007

| Quantiles q | 1993 | 1999 | 2007 | % Q-change 1993–1999 | % Q-change 1999–2007 | % Q-change 1993–2007 |
|---|---|---|---|---|---|---|
| 0.10 | 0.10 | 0.15 | 0.17 | 53% | 8% | 64% |
| 0.20 | 0.29 | 0.38 | 0.43 | 31% | 11% | 46% |
| 0.30 | 0.66 | 0.81 | 0.97 | 23% | 20% | 47% |
| 0.40 | 1.14 | 1.22 | 1.58 | 6% | 30% | 38% |
| 0.50 | 2.04 | 2.23 | 2.77 | 9% | 24% | 36% |
| 0.60 | 3.58 | 3.92 | 4.57 | 10% | 16% | 28% |
| 0.70 | 5.85 | 5.89 | 6.18 | 1% | 5% | 6% |
| 0.80 | 7.48 | 7.91 | 8.06 | 6% | 2% | 8% |
| 0.90 | 11.24 | 10.60 | 11.75 | -6% | 11% | 5% |

Source: Produced by the authors based on World Bank (2013).

Note: quantile refers to countries' percentage. So $Q_{0.10}$ in 2007 means 10% of world countries had $CO_2$ emissions per capita below 0.17 t.

## Table 2. Descriptive statistics of explanatory factors

| **Variable (1993)** | **Obs** | **Mean** | **Std. Dev.** | **CV** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| CO2 emissions (ktonnes per capita) | 189 | 4,739.77 | 7,031.45 | 1.48 | 1.69 | 62,517.04 |
| ln (CO2 emissions per capita) | 189 | 7.35 | 1.83 | | 0.53 | 11.04 |
| per capita GDP (constant 2000 US$) | 187 | 6,423.19 | 10,135.28 | 1.58 | 79.58 | 68,695.23 |
| Agriculture GDP share (%) | 165 | 19.43 | 16.23 | 0.83 | - | 65.12 |
| Industrial GDP share (%) | 166 | 29.02 | 10.98 | 0.38 | 8.70 | 64.00 |
| Urban population share (%) | 210 | 52.82 | 24.67 | 0.47 | 6.84 | 100.00 |
| Non dependent population share (aged 15 to 65) | 190 | 59.08 | 6.71 | 0.11 | 45.53 | 72.13 |
| Average daily min temperature | 198 | 13.67 | 8.66 | 0.63 | - 22.60 | 25.30 |

| **Variable (1999)** | **Obs** | **Mean** | **Std. Dev.** | **CV** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| CO2 emissions (ktonnes per capita) | 195 | 4,622.44 | 6,401.30 | 1.38 | 15.23 | 55,114.07 |
| ln (CO2 emissions per capita) | 195 | 7.46 | 1.66 | | 2.72 | 10.92 |
| per capita GDP (constant 2000 US$) | 196 | 7,511.32 | 11,999.97 | 1.60 | 95.50 | 74,111.49 |
| Agriculture GDP share (%) | 171 | 17.41 | 15.61 | 0.90 | - | 76.19 |
| Industrial GDP share (%) | 172 | 28.78 | 11.96 | 0.42 | 7.20 | 79.99 |
| Urban population share(%) | 210 | 54.58 | 24.55 | 0.45 | 8.08 | 100.00 |
| Non dependent population share (aged 15 to 65) | 190 | 60.41 | 6.52 | 0.11 | 48.14 | 72.74 |
| Average daily min temperature | 198 | 13.67 | 8.66 | 0.63 | - 22.60 | 25.30 |

| **Variable (2007)** | **Obs** | **Mean** | **Std. Dev.** | **CV** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| CO2 emissions (ktonnes per capita) | 198 | 5,096.36 | 6,849.85 | 1.34 | 22.61 | 57,660.25 |
| ln (CO2 emissions per capita) | 198 | 7.58 | 1.66 | | 3.12 | 10.96 |
| per capita GDP (constant 2000 US$) | 194 | 9,191.87 | 14,631.59 | 1.59 | 96.25 | 98,397.09 |
| Agriculture GDP share (%) | 169 | 12.53 | 12.28 | 0.98 | - | 54.99 |
| Industrial GDP share (%) | 171 | 31.11 | 14.10 | 0.45 | 5.86 | 94.58 |
| Urban population share(%) | 210 | 56.99 | 24.16 | 0.42 | 10.10 | 100.00 |
| Non dependent population share (aged 15 to 65) | 190 | 62.94 | 6.87 | 0.11 | 48.81 | 82.22 |
| Average daily min temperature | 198 | 13.67 | 8.66 | 0.63 | - 22.60 | 25.30 |

Source: Produced by the authors based on World Bank (2013).

Note: further descriptive data is available upon request. The most recent available climate standard normal has been used as climatic reference of the country.

**Table 3. Results from auxiliary OLS regressions on $CO_2$ per capita and explanatory factors, 1993–2007**

| Variable | 1993 | 1995 | 1997 | 1999 | 2001 | 2003 | 2005 | 2007 |
|---|---|---|---|---|---|---|---|---|
| **Affluence** | | | | | | | | |
| GDP per capita | .00022778** | .00021738*** | .00015367** | .00015564*** | .00015664*** | .00016302*** | .00016393*** | .00016841*** |
| Squared GDP per capita | -1.431e-08** | -1.322e-08*** | -8.516e-09** | -8.346e-09** | -7.730e-09*** | -7.707e-09*** | -7.461e-09*** | -7.006e-09*** |
| Cubic GDP per capita | 2.497e-13** | 2.243e-13** | 1.346e-13* | 1.278e-13** | 1.116e-13*** | 1.087e-13*** | 9.962e-14*** | 8.448e-14*** |
| **Sectoral Composition** | | | | | | | | |
| Agric. GDP share (%) | -.01342054* | -.02222722*** | -.02916964*** | -.02927415*** | -.02897955*** | -.02527107*** | -.02486403*** | -.03068516*** |
| Indust. GDP share (%) | .0347483*** | .03459411*** | .02564298*** | .018115*** | .02332022*** | .02433404*** | .01680331*** | .01653982*** |
| **Population Structure** | | | | | | | | |
| Urban population share | .01733784*** | .01225186*** | .00822251** | .00671887* | 0.00546392 | .00571538* | .00623419* | 0.00337771 |
| Non-dependent pop. | .07808158*** | .06992016*** | .08566869*** | .09595006*** | .10306478*** | .10293884*** | .10317962*** | .08912037*** |
| **Climate** | | | | | | | | |
| Av. daily min. temp. | -.02463132** | -.02426302*** | -.02362798*** | -.02221845*** | -.01600683** | -.01564607** | -.01747623** | -.02104922*** |
| **Constant** | 0.9419073 | 1.8809878** | 1.5956777* | 1.1516657 | 0.42887263 | 0.23336353 | 0.31073141 | 1.3898487* |
| Countries[1] | 154 | 161 | 161 | 160 | 163 | 165 | 161 | 155 |
| Squared R | 0.79798729 | 0.84017732 | 0.85189569 | 0.84314694 | 0.85502122 | 0.8497542 | 0.84449959 | 0.84741744 |
| Adjusted Squared R | 0.78684176 | 0.8317656 | 0.84410073 | 0.83483684 | 0.84748985 | 0.84204928 | 0.83631536 | 0.83905675 |
| log-likelihood | -183.69907 | -165.53358 | -154.45728 | -157.2094 | -155.9453 | -159.37318 | -154.28651 | -138.8818 |

Note: * p<.1; ** p<.05; *** p<.01

Source: Produced by the authors based on World Bank (2013).

**Table 4. Relative factor contribution to inequality in $CO_2$ per capita**

| Factors | 1993 | 1995 | 1997 | 1999 | 2001 | 2003 | 2005 | 2007 |
|---|---|---|---|---|---|---|---|---|
| **Affluence** | **14.87** | **15.91** | **13.13** | **13.95** | **15.84** | **17.84** | **18.71** | **21.44** |
| **Sectoral Composition** | **19.72** | **28.71** | **30.85** | **27.54** | **27.70** | **24.66** | **21.05** | **24.36** |
| agriculture GDP share | 8.86 | 16.66 | 22.38 | 22.30 | 20.74 | 17.47 | 16.64 | 19.80 |
| Industrial GDP share | 10.86 | 12.05 | 8.47 | 5.24 | 6.96 | 7.19 | 4.42 | 4.55 |
| **Population Structure** | **39.67** | **34.05** | **35.68** | **37.51** | **38.53** | **39.14** | **40.64** | **33.88** |
| Urban pop. Share | 17.39 | 12.99 | 8.76 | 7.00 | 5.51 | 5.65 | 6.11 | 3.24 |
| Non-dependent pop. | 22.27 | 21.05 | 26.92 | 30.51 | 33.02 | 33.49 | 34.54 | 30.64 |
| **Climate** | **5.55** | **5.35** | **5.54** | **5.31** | **3.44** | **3.33** | **4.04** | **5.06** |
| **Residual** | **20.20** | **15.98** | **14.81** | **15.69** | **14.50** | **15.02** | **15.55** | **15.26** |
| **Total** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |

Source: Produced by the authors based on World Bank (2013).

**Table 5. Decomposition of the contribution of each factor to inequality changes into coefficient and dispersion effects**

| | Contrib. Change | Dispersion effect | | Coefficient effect | |
|---|---|---|---|---|---|
| **1993–1997** | | | | | |
| Affluence | -0.0173 | 0.0199 | -115% | -0.0371 | 215% |
| Agriculture GDP share (%) | 0.1343 | 0.0143 | 11% | 0.1201 | 89% |
| Industrial GDP share (%) | -0.0236 | 0.0063 | -26% | -0.0299 | 126% |
| Non-dependent population share (aged 15 to 65) | 0.0462 | 0.0225 | 49% | 0.0237 | 51% |
| Urban population share (%) | -0.0858 | 0.0107 | -12% | -0.0965 | 112% |
| Average daily min. temperature | -0.0001 | 0.0023 | -3887% | -0.0023 | 3987% |
| Residual | -0.0538 | -0.0538 | 100% | 0.0000 | 0% |
| **1997–2003** | | | | | |
| Affluence | 0.046 | 0.011 | 24% | 0.035 | 76% |
| Agriculture GDP share (%) | -0.049 | -0.022 | 45% | -0.027 | 55% |
| Industrial GDP share (%) | -0.013 | -0.009 | 70% | -0.004 | 30% |
| Non-dependent population share (aged 15 to 65) | 0.065 | 0.010 | 15% | 0.056 | 85% |
| Urban population share (%) | -0.031 | -0.006 | 20% | -0.025 | 80% |
| Average daily min. temperature | -0.022 | -0.024 | 111% | 0.002 | -11% |
| Residual | 0.003 | 0.003 | 100% | 0.000 | 0% |
| **2003–2007** | | | | | |
| Affluence | 0.036 | 0.031 | 86% | 0.005 | 14% |
| Agriculture GDP share (%) | 0.023 | -0.012 | -50% | 0.035 | 150% |
| Industrial GDP share (%) | -0.026 | -0.005 | 19% | -0.021 | 81% |
| Non-dependent population share (aged 15 to 65) | -0.028 | 0.019 | -66% | -0.047 | 166% |
| Urban population share (%) | -0.024 | -0.002 | 7% | -0.022 | 93% |
| Average daily min. temperature | 0.017 | 0.004 | 25% | 0.013 | 75% |
| Residual | -0.005 | -0.005 | 100% | 0.0000 | 0% |
| **1993–2007** | | | | | |
| Affluence | 0.0648 | 0.1267 | 195% | -0.0619 | -95% |
| Agriculture GDP share (%) | 0.1087 | -0.0020 | -2% | 0.1107 | 102% |
| Industrial GDP share (%) | -0.0626 | -0.0128 | 21% | -0.0498 | 79% |
| Non-dependent population share (aged 15 to 65) | 0.0832 | 0.0455 | 55% | 0.0377 | 45% |
| Urban population share (%) | -0.1406 | -0.0075 | 5% | -0.1331 | 95% |
| Average daily min. temperature | -0.0048 | 0.0038 | -79% | -0.0086 | 179% |
| Residual | -0.0487 | -0.0487 | 100% | 0.0000 | 0% |

Source: Produced by the authors based on World Bank (2013).

## Table 6. Contribution of factors to the change in inequality measured by log-variance (%)

| Factors | 1993–1999 | 1999–2007 | 1993–2007 |
|---|---|---|---|
| **Affluence** | **24.48** | **-233.27** | **-15.19** |
| **Sectoral Composition** | **-62.14** | **132.67** | **-1.50** |
| Agriculture GDP share | -131.79 | 104.81 | -41.20 |
| Industrial GDP share | 69.65 | 27.86 | 39.70 |
| **Population Structure** | **62.24** | **157.21** | **66.12** |
| Urban pop. Share | 126.16 | 131.09 | 82.14 |
| Non-dependent pop. | -63.92 | 26.12 | -16.02 |
| **Climate** | **7.96** | **13.61** | **7.75** |
| **Residual** | **67.46** | **29.78** | **42.82** |
| **Total** | 100.00 | 100.00 | 100.00 |
| ***Total change in log-variance*** | *-9* | *-10* | *-18* |

Note: The last row shows the total change in inequality for the different periods. The rest of the rows show the percentage of this change that is attributable to each factor.

Source: Produced by the authors based on World Bank (2013).