# Statistical polarization in greenhouse gas emissions: Theory and evidence

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**Abstract**

The current debate on climate change is over whether global warming can be limited in order to lessen its impacts. In this sense, evidence of a decrease in the statistical polarization in greenhouse gas (GHG) emissions could encourage countries to establish a stronger multilateral climate change agreement. Based on the interregional and intraregional components of the multivariate generalised entropy measures (Maasoumi, 1986), Gigliariano and Mosler (2009) proposed to study the statistical polarization concept from a multivariate view. In this paper, we apply this approach to study the evolution of such phenomenon in the global distribution of the main GHGs. The empirical analysis has been carried out for the time period 1990-2011, considering an endogenous grouping of countries (Aghevli and Mehran, 1981; Davies and Shorrocks, 1989). Most of the statistical polarization indices showed a slightly increasing pattern that was similar regardless of the number of groups considered. Finally, some policy implications are commented.

**Keywords:** Climate Change, Greenhouse Gas Emissions, Multivariate Statistical Polarization, Generalised Entropy Indices.

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## 1. Introduction

Climate change is one of the most important challenges facing the international community nowadays. Given its possible far-reaching consequences for ecosystems and the quality of life of hundreds of millions of people, climate change is a political issue on the global agenda as it was firmly established in the Third and Fourth Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC, 2001, 2007).

The principal causes of global warming are the anthropogenic emissions of greenhouse gases (GHGs), especially carbon dioxide ($CO_2$) from fossil fuel combustion. However, emissions of non-$CO_2$ GHGs, such as methane ($CH_4$), nitrous oxide ($N_2O$) and fluorinated gases (F-gases), also alter significantly the climate. A recent *Greenhouse Gas Bulletin* (World Meteorological Organization, 2016) shows that the concentration of $CO_2$, $CH_4$, $N_2O$ has increased by 144, 256 and 121 percent since the year 1750, respectively. The increase in global $CO_2$ concentration is basically due to the fossil fuel combustion. $CH_4$ is emitted into the atmosphere from both natural (about 40 percent) and anthropogenic sources (approximately 60 percent). In the case of $N_2O$, close to 60 percent is emitted into the atmosphere by natural sources and about 60 percent comes from human activities. Although F-gases are still low in abundance, they are potent GHGs which are increasing at relatively rapid rates given its anthropogenic origin.

Given that non-$CO_2$ GHGs contribute more to global warming per unit mass than $CO_2$ (U.S. Environmental Protection Agency, 2012) and to reduce them is a relatively cheap complement to the cost associated to $CO_2$-only mitigation (U.S. Environmental Protection Agency, 2006), these gases have an important function in limiting global climate change. In addition, as these gases have much shorter lifetimes than $CO_2$, reducing their emissions offers an extra opportunity to curb climate change (Montzka et al., 2011; Weyant et al. 2006; Rao and Riahi 2006).

In recent years the concept of statistical polarization has emerged to capture the inherent conflict or instability of a distribution. While inequality measures study the dispersion of a distribution with respect to a reference value, the statistical examination of polarization consists in identifying the appearance of poles in that distribution, which is related to multimodal distributions (Esteban and Ray, 1994; Wolfson, 1994). According to a specific attribute, the notion of statistical polarization considers the population divided into different groups so that, the groups are internally homogeneous but different each other.

In the environmental field, global negotiations on reducing emissions are constructed through alliances of groups of countries with conflicting interests. Thus, developed and developing countries have polarized positions given their different environmental responsibilities and level of development. Some experts have suggested that climate change will intensify resource scarcity, population displacements and fuel conflicts, being these effects particularly serious in developing countries where infrastructure is missing (Salehyan, 2008).

Given that climate change may cause conflicts between the haves and the have-nots, increasing even global inequality, international statistical polarization using only one gas has already been analysed in various studies. Thus, Ezcurra (2007) analysed the convergence in per capita $CO_2$ emissions using the *EGR* indices for the period 1960-1999. Meanwhile, Duro and Padilla (2008) used this same measure to investigate the same fact between 1971 and 2001. Duro (2010) examined the statistical polarization in per capita $CO_2$ emissions with exogenous groups based on the *Z–K* measure (Zhang and Kanbur, 2001), whose main differential advantage lies in its factor-decomposability. Duro and Padilla (2013) analysed the degree of statistical polarization in the international distribution of per capita $CO_2$ emissions in the European Union, where the countries are grouped according to two criteria: their similarity in terms of emissions –endogenously– and their geographical location –exogenously. Finally, Duro and Teixidó-Figueras (2014) explored the distribution of per capita $CO_2$ emissions for the period 1992-2010 comparing different statistical polarization measures.

The principal limitation of the previous studies is that they only consider the distribution of $CO_2$ emissions, not giving a real picture of the international situation. In this sense, the extension of the preceding works to the analysis of the international distribution of the main GHG emissions is quite useful. On the one hand, it would give complete information about the possible political consequences of the emissions distribution, in terms of conflicts, and the probability of implementing international agreements. On the other hand, it would also give new insights of the Ecological Unequal Exchange framework[1].

Using the multivariate inequality measures proposed by Maasoumi (1986), and considering their decomposition into the between- and within-group inequality components, it is possible to obtain statistical polarization indices from a multivariate perspective (Gigliariano and Mosler, 2009). The main aim of this article is therefore to apply these indices to study the international statistical polarization in the distribution of the principal GHG emissions: $CO_2$, $CH_4$, $N_2O$ and F-gases. Specifically, the empirical analysis is carried out for the time period 1990-2011 considering an endogenous grouping of countries (Aghevli and Mehran, 1981; Davies and Shorrocks, 1989). Moreover, this

[1] The Ecological Unequal Exchange theory refers to the structurally determined disparity of natural resource consumption between the core and peripheral countries within the world-system (Hornborg, 2011) and its empirical analysis has become quite popular (see Teixidó-Figueras and Duro, 2014; Moran et al., 2013; Niccolucci et al., 2012; among others).

paper is an extension of the results recently obtained by Remuzgo et al. (2016) on the study of the evolution of global inequality in GHG emissions from 1990 to 2011.

To the best of our knowledge, this is the first attempt to use multivariate statistical polarization measures for analysing, in a joint manner, the global distribution of GHG emissions[2]. In this sense, the use of quantitative methods for analysing the historical trend of global statistical polarization in GHG emissions is a significant step towards solving the problem of climate change. Moreover, modelling the social effects of global warming will facilitate the dialogue on this issue between national governments, international organizations, non-profit groups and multinational firms in order to design effective global polices.

The rest of the paper is organised as follows. Section 2 examines the concept of statistical polarization, including the principal measures proposed in the literature. Next, the multivariate statistical polarization indices used in this paper are detailed. The main results of the analysis are exposed in sections 4 and 5. Finally, with the conclusions of the chapter, some policy implications are discussed.

## 2. The concept of statistical polarization

Inequality measures quantify the dispersion of a distribution with respect to a reference value –usually the arithmetic mean. However, to study some social phenomena is interesting to use a measure of the degree to which population is clustered around a number of poles at a certain distance. The concept of statistical polarization (hereinafter referred to as polarization) is directly related to the emergence of social tensions caused

[2] Using a different approach, Duro (2016) analysed the international distribution of GHG emissions both at global level and considering their three main sources –$CO_2$, $CH_4$ and $N_2O$– for the period 1990-2012.

by a general dissatisfaction (Esteban and Ray, 1994; Wolfson, 1994). In statistical terms, the phenomenon of polarization leads to a distribution with more than one mode (Ezcurra et al., 2006).

The studies of polarization make possible to capture the potential conflict related to a given distribution. Thus, social tensions are more likely in a population distributed around two poles, that is, in a population divided into two groups of significant size with distinct characteristics. On the contrary, in a population with a high level of inequality, where a single individual has a characteristic opposite to that which is shared by the rest of the population, the development of social conflicts is not relevant. Polarization is enhanced when it is observed in the distribution a small number of groups of similar size, characterized by a high degree of internal homogeneity and heterogeneity among all of them.

In order to understand the concept of statistical polarization, the following example is considered. Suppose a population composed of six countries whose emissions levels are 2, 3, 4, 5, 6 and 7 tonnes, respectively. Next, assume that through transfers we have a two-point distribution concentrated equally on the emission levels 1 and 8. As illustrated in Figure 1, the transfers of emissions lead to a distribution with only two levels of contamination: three countries pollute 1 tonne and the other three pollute 8 tonnes. Now, the society is divided into two distinct groups, that is, a polarized world in which the emergence of social conflicts is more likely. This is the result of the combination of two processes: identification and alienation[3]. On the one hand, the identification process is related to a high degree of homogeneity within each group, that is, each country feels

[3] Although the concepts of inequality and polarization are linked to the study of disparities in a distribution, the inequality approach only captures the second part of the identification-alienation framework.

some degree of identification with those countries which have a similar emission level. On the other hand, the alienation process is linked with a high degree of heterogeneity between groups; in other words, one country feels alienated from those whose level of emissions is faraway. In this manner, the existence of a small groups is not relevant in the study of polarization (Gradín and Del Río, 2001).

(Place Figure 1 here)

In recent decades, several authors have proposed different indices of polarization, providing another perspective –additional to the inequality approach– to analyse the distribution of a phenomenon of interest. The best known polarization index was formulated by Esteban and Ray (1994) and its expression is:

$$ER(\alpha) = \sum_{i=1}^{n} \sum_{j=1}^{n} p_i^{1+\alpha} p_j \left| \frac{x_i}{\mu} - \frac{x_j}{\mu} \right|, \quad 1 \le \alpha \le 1.6, \qquad (1)$$

where $x_i$ and $x_j$ represent the per capita emissions of the countries belonging to the groups $i$ and $j$, respectively; $p_i$ and $p_j$ are the relative populations of the countries belonging to the groups $i$ and $j$, respectively; $\mu$ is the world average of per capita emissions and $\alpha$ shows the level of sensitivity to polarization[4]. This parameter makes a difference between inequality and polarization measures, since a greater value of $\alpha$ implies that the measure is more sensitive to the concentration in groups[5]. The lower and upper limits of the index are 0 and 1, respectively (Esteban, 1996).

The main limitation of the *ER* index is that groups are predetermined, so it is not plausible to make groups of countries based on a specific criterion. Given the previous restriction,

[4] The $\alpha$ parameter falls in the interval [1-1.6] in order to be consistent with a set of axioms.

[5] The smaller the sensitivity parameter, the closer the notion of polarization to inequality. Indeed, when $\alpha = 0$, the *ER* index is a scalar transformation of the Gini index.

Esteban et al. (1999) proposed the *ERG* index which allows to define groups endogenously:

$$ERG(\alpha,\beta) = ER(\alpha) - \beta(G - G_B), \quad 1 \le \alpha \le 1.6, \beta \ge 0, \tag{2}$$

where $ER(\alpha)$ is the Esteban and Ray's index of polarization; $G$ is the Gini coefficient of the original distribution; $G_B$ is the Gini coefficient of the clustered distribution (inequality between groups); and $\beta$ parameter measures the sensitivity to the internal cohesion of the groups (Esteban, 2002). It is reasonable that $\beta$ takes a value close to 1 in order not to alter the scale of the measure.

The difference between the Gini indices includes the error caused by the heterogeneity within each group. In this case, both the choice of the number of poles and the location of the same remain exogenous. Although the *ERG* index is not uniformly bounded, a value close to 1 can be interpreted as a scenario of high polarization, while a value close to 0 would be indicative of low polarization.

Alternatively, Wolfson (1994, 1997) proposed the following polarization index:

$$P^W = \frac{\mu}{m}\left(\frac{1}{2} - L\left(\frac{1}{2}\right) - \frac{G}{2}\right), \tag{3}$$

where $\mu$, $m$, $L$ and $G$ are the mean, the median, the Lorenz curve and the Gini index of the distribution. This measure is a particular case of the *EGR* index when the $\alpha$ and $\beta$ parameters take unit values (Esteban et al., 1999). Its main limitation is that it only makes sense in the case of bipolarization, so it does not allow us to examine multimodal distributions.

In this section we have presented several polarization indices which only consider one variable. Next, we will focus on describing the same phenomenon from a multivariate perspective. Thus, multivariate measures of polarization consider two or more characteristics in the establishment of the groups (Esteban and Ray, 2012). In this case, both identity and distances/alienation are measured from several variables of interest (Duclos and Taptué, 2015).

In this sense, the multivariate polarization measure proposed by Zhang and Kanbur (2001) –based on the family of the entropy indices developed by Theil– is given by the following expression:

$$P^{ZK} = \frac{\sum_{g=1}^{G} \log \frac{\mu}{\mu_g} \pi_g}{\sum_{g=1}^{G} \pi_g \; I(f_g)}, \tag{4}$$

where $\mu$ is the world average of per capita emissions; $\mu_g$ represents the average of per capita emissions of the countries belonging to the group $g$; $\pi_g$ denotes the relative population of the countries belonging to the group $g$ and $I(f_g)$ is the inequality in the $g$th group.

Anderson (2010) proposed two alternative multivariate relative polarization measures for the case of bipolarization (two groups that are named as $g_1$ and $g_2$, respectively). The first index is called "overlap measure" and it is defined by:

$$OV = \int_x \min\{ f_{g_1}(\underline{\mathbf{x}}) f_{g_2}(\underline{\mathbf{x}})\} d\underline{\mathbf{x}}, \tag{5}$$

where $\underline{\mathbf{x}}$ is the vector of characteristics, $\underline{\mathbf{x}} = (x_1, x_2, \ldots, x_k)$, and it is assumed that the two population groups are distributed according to two continuous multivariate unimodal distributions, $f_{g_1}(\underline{\mathbf{x}})$ and $f_{g_2}(\underline{\mathbf{x}})$, respectively.

Furthermore, Anderson (2010) proposed another index which does not depend on overlap and can be therefore implemented when attributes are mutually exclusive. This measure is called "polarization trapezoid" and can be expressed as follows:

$$BIPOL = 0.5\left\{ f_p(\underline{\mathbf{x}}_{mg_1}) + f_r(\underline{\mathbf{x}}_{mg_2})\right\}\frac{1}{\sqrt{K}}\sqrt{\sum_{j=1}^{K}\frac{(x_{mg_1k} - x_{mg_2k})^2}{\mu_k}}, \quad (6)$$

where $\underline{\mathbf{x}}_{mg_1}$ and $\underline{\mathbf{x}}_{mg_2}$ are the modal vectors for the two groups, respectively; $x_{mg_1k}$ and $x_{mg_2k}$ are the modal points in the $k$th characteristic for the two groups, respectively; $\mu_k$ represents the average of the modes in the $k$th characteristic and $K$ are the variables identified. This index represents the area of the trapezoid formed by the heights of the two distributions at their modal points and the mean normalized Euclidean distance between the two modal points.

Meanwhile, Gigliariano and Mosler (2009) developed a family of multivariate polarization indices based on the assumption that internal homogeneity, external heterogeneity, and similarity of group sizes are captured. In this approach the measurement of group homogeneity/heterogeneity is enhancing through multivariate distances. It should be noted that, as it is detailed in next section, these polarization indices are built from decomposable indices of multivariate inequality indices and from measures of relative groups size.

## 3. Methodology and data

The methodology applied in the multivariate polarization study is described in this section. In order to construct multivariate polarization indices, we proceed in two stages. In the first phase, the multivariate inequality indices based on the concept of generalised entropy are obtained, which can be expressed as the sum of the within and the between inequality components (Maasoumi, 1986 and Maasoumi and Nickelsburg, 1988). Using the previous decomposition, the multivariate polarization indices developed by Gigliariano and Mosler (2009) are calculated in a second stage.

### 3.1 Stage I: Obtaining multivariate inequality indices

In order to obtain the multivariate inequality indices, it is considered $K$ variables which are linked to climate change. In particular, these variables are collected from a sample of $N$ countries as it is shown in the matrix **X**:

$$\mathbf{X} = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1K} \\ \vdots & & \vdots & & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iK} \\ \vdots & & \vdots & & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NK} \end{bmatrix}, \tag{7}$$

where $x_{ij}$ denotes the per capita emissions of the main GHGs –$CO_2$, $CH_4$, $N_2O$ and F-gases–, taking $K$ the value 4.

As we want to study the inequality, we use the multivariate inequality indices (Maasoumi, 1986) which are expressed as:

$$GEM_{\gamma}(\mathbf{X}) = \frac{1}{\gamma\,(1+\gamma)} \frac{1}{N} \sum_{i=1}^{N} \left[ \left( \frac{s_i}{\bar{s}} \right)^{1+\gamma} - 1 \right], \quad \gamma \neq -1, 0. \tag{8}$$

The $\gamma$ parameter symbolises the importance attributed to the emission transfers that may occur in the different parts of the distribution. In such a way, as $\gamma$ increases, the most polluting countries receive more weight in the index.

We have two special cases when $\gamma$ is set to -1 –more weight is assigned to the least contaminant countries– and 0 –all countries receive the same importance–. In these scenarios the indices are defined, respectively, as:

$$GEM_{-1}(\mathbf{X}) = \frac{1}{N} \sum_{i=1}^{N} \log\left( \frac{\bar{s}}{s_i} \right), \tag{9}$$

and

$$GEM_0(\mathbf{X}) = \frac{1}{N}\sum_{i=1}^{N}\frac{s_i}{\bar{s}}\log\left(\frac{s_i}{\bar{s}}\right). \tag{10}$$

In all cases, we use a generalised mean of order minus $\beta$ to sum the different variables:

$$s_i = \left(\sum_{j=1}^{K}\delta_j x_{ij}{}^{-\beta}\right)^{-1/\beta}, \quad i = 1, \ldots, N, \tag{11}$$

where $\bar{s}$ is the arithmetic mean of the values $s_i$.

Additionally, the $\delta_j$ ($j$ = 1, …, $K$, $0 \leq \delta_j \leq 1$) parameter denotes the weight assigned to each variable $j$ in the overall index, and the $\beta$ ($-1 \leq \beta \leq \infty$) parameter represents the elasticity of substitution among the different gases.

In order to show the correspondence between the effect of the different GHGs it is fundamental to consider both their relative contribution to the global warming and the amount of each gas emitted into the atmosphere. In this sense, there is a need of assuming some kind of "substitutability of natural capital" between the different emissions, that is, as if the emissions of one gas could be replaced by the ones from another contaminant. Therefore, all the emissions[6] are expressed in million tonnes of $CO_2$-equivalent ($MtCO_2e$)[7], being possible to compare directly the effect of all of them.

[6] The data have been extracted from the Climate Analysis Indicators Tool database (CAIT, 2014), developed and updated by the World Resources Institute.

[7] It is used the 100-year GWPs published in the IPCC (1996) in accordance with the United Nations Framework Convention on Climate Change (UNFCCC). However, some authors such as Tol et al. (2008) argue that the UNFCCC should use a cost-effectiveness framework –such as, the Global Cost Potential or the Global Temperature Potential– instead of the cost-benefit analysis that involves the GWP.

The importance attached to each contaminant is related to the share of the atmospheric concentration of each gas in the year 2011[8], also measured in $CO_2$-equivalent using the 100-year GWPs published in the IPCC (1996). In particular, the $\delta$ parameter takes the value of 0.7394, 0.0955, 0.1624 and 0.0028 for the $CO_2$, $CH_4$, $N_2O$ and F-gases, respectively.

Given that the inequality index takes into account the two necessary characteristics to compare the emissions of different GHGs, it is considered that $\beta$ = -1, that is, there is perfect substitution among pollutants. Meanwhile, to begin with, the $\gamma$ parameter has been fixed to 0 giving the same importance to all the countries.

Multivariate inequality measures used ($GEM_\gamma$, $GEM_{-1}$ and $GEM_0$) can be additively decomposable by population sub-groups, allowing the analysis of the level of inequality between and within the different regions considered. Whereas inequality between groups just collects the dissimilarities between average inequalities of each region, the within groups component focuses on the inequality between the countries included in the same region. According to the methodology proposed by Maasoumi (1986) and Maasoumi and Nickelsburg (1988), the $GEM_\gamma$ index can be additively decomposed in the following way:

$$GEM_\gamma(\mathbf{X}) = B_\gamma(\mathbf{X}) + W_\gamma(\mathbf{X}), \tag{12}$$

where $B_\gamma(\mathbf{X})$ denotes the between-group inequality component:

$$B_\gamma(\mathbf{X}) = f\left(\sum_{g=1}^{G} \frac{N_g}{N} h\,(\bar{s}^g, \bar{s})\right), \tag{13}$$

[8] It has been considered the concentration of GHGs in the year 2011 as reference because it is the last year with available data. In particular, the IPCC (2013) reported that the concentration of $CO_2$, $CH_4$, $N_2O$ and F-gases in 2011 was 391000000, 1803000, 324000 and 210.04 parts per trillion, respectively.

and $W_{\gamma}(\mathbf{X})$ is the within-group inequality component:

$$W_{\gamma}(\mathbf{X}) = \sum_{g=1}^{G} w_g \, f\left( \frac{1}{N_g} \sum_{i \in g} h\,(s_i, \bar{s}^g) \right), \tag{14}$$

where $N_g$ is the number of countries which are part of the region $g$; $w_g$ is the weight associated with the region $g$ and, finally, $G$ is the number of regions considered in the analysis. Additionally, $f$ and $h$ functions are continuous functions, being $f$ strictly increasing. The components of these indices for the different values of the $\gamma$ parameter, are shown in Table I, where $s_i = \left(\sum_{j=1}^{K} \delta_j x_{ij}^{-\beta}\right)^{-1/\beta}, i \in g;$ $\bar{s}$ is the arithmetic mean of the values $s_i$ and $\bar{s}^g$ is the arithmetic mean of the values $s_i$ over the countries in region $g$.

(Place Table I here)

### 3.2 Stage II: Multivariate statistical polarization indices calculation

Gigliriano and Mosler (2009) proposed different polarization indices using the decomposition of the previous multivariate inequality measures ($GEM_{\gamma}$, $GEM_{-1}$ and $GEM_0$) into the between and within-group inequality components.

Thus, keeping the previous notation, three different specifications for the polarization indices are considered[9]:

$$P_1(\mathbf{X}) = \phi\left( \frac{B(\mathbf{X})}{W(\mathbf{X}) + c} \right) \cdot S(\mathbf{X}), \tag{15}$$

$$P_2(\mathbf{X}) = \phi\big(B(\mathbf{X}) - W(\mathbf{X})\big) \cdot S(\mathbf{X}), \tag{16}$$

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[9] The parameter $c$ has to be positive and depends on the values of $B$(**X**) and $W$(**X**). In this case, the value 0.1 has been considered appropriate.

$$P_3(\mathbf{X}) = \phi\left(\frac{B(\mathbf{X})}{B(\mathbf{X}) + W(\mathbf{X}) + c}\right) \cdot S(\mathbf{X}), \tag{17}$$

taking into account that,

$$S(\mathbf{X}) = \left[\left(\prod_{g=1}^{G}\left(\frac{N_g}{N}\right)^{-\frac{N_g}{N}}\right) - 1\right] \cdot \frac{1}{G-1}, \; g = 1,\ldots,G. \tag{18}$$

and $\phi(\mathbf{X}) = \mathbf{X},$ given that $\phi(\mathbf{X})$ must be a continuous and strictly increasing function.

## 4. Multivariate inequality analysis

The multivariate indices used in this paper can be additively decomposed by population sub-groups. In this paper, the creation of groups has been made using the method proposed by Aghevli and Mehran (1981), technique which was later refined by Davies and Shorrocks (1989). This procedure involves minimizing disparities within each group considered. For this purpose, it is necessary to calculate the average emission between adjacent groups to find the border between them. This process converges to two extreme solutions which, in case of not coinciding, delimit all the possibilities of grouping.

The difference from previous applications of this method of grouping lies in the use of the generalised entropy measures, instead of the Gini index, to analyse inequality between groups. Thus, to determine which number of groups is the most appropriate for explaining the degree of polarization, the percentage of total inequality that can be explained by the between-group inequality component ($B_\gamma(\mathbf{X}) / GEM_\gamma(\mathbf{X})$) is calculated in each case. It should be highlighted that, although the consideration of a large number of poles allows us to explain a greater percentage of total inequality, it reduces, at the same time, the interest of the polarization analysis.

Regarding the groups of countries considered in this analysis, the level of emissions released into the atmosphere in 2011 by each country has been taken into account in order to keep a consistent sample for the entire period. In particular, this analysis is carried out considering the sample divided into four ($G$ = 4) and eight groups ($G$ = 8). In this case, four is the minimum number of groups that allows the between-group inequality component to explain, at least, 70 percent of total inequality in all the years. Meanwhile, eight is the maximum number of groups admitted in this study given that from this number onwards the percentage of total inequality explained by the between-group inequality component was similar and, therefore, increasing the number of poles did not involve an important explanatory improvement (see Table II).

(Place Table II here)

Figure 2 illustrates which countries belong to each group after applying the endogenous method of grouping mentioned before[10]. Figure 3 presents the multivariate inequality indices for the four main pollutants over the period 1990-2011. It also exposes the decomposition of the multivariate indices by population sub-groups. The solid line represents the total inequality value, the large-dashed line displays the inequality between groups and the short-dashed line exhibits the within-group inequality component.

(Place Figure 2 here)

Considering that all countries are equally weighted ($\gamma$ = 0) and a perfect elasticity of substitution among gases ($\beta$ = -1), total inequality in GHG emissions remained constant over the period 1990-2011. An increasing pattern is observed until 1994; holding the opposite tendency until the year 1997. The maximum level of inequality was reached in

[10] The classification of the countries can be found in the Appendixes A and B.

the year 2005, followed by a decreasing path until 2009, and a stabilization in the last two years of study.

In both cases, when the distribution was divided into four and eight groups, the two inequality components showed a similar pattern between 1990 and 2011. Although both components contributed to the change in overall inequality from 1990 to 2011, the interregional inequality prevailed in the two scenarios.

(Place Figure 3 here)

The between-group inequality component showed an increasing trend from 1990 to 2011, however, such increment was bigger when it was considered more groups of countries. Thus, whereas this kind of inequality increased by 22 percent when $G = 4$, the same suffered an increment of 7 additional percentage points when $G = 8$.

In relation to the within-group inequality component, a decreasing tendency was perceived, being much more accentuated when it was taken into account eight groups of countries –roughly 88 percent. These results are coherent given that the bigger the number of groups considered, the higher (smaller) the inequality between (within) groups.

Figure 4 presents the contribution to this phenomenon of the inequality within groups for different values of the $\gamma$ and $\beta$ parameters[11] in 1990 and 2011 considering four and eight groups, respectively. This analysis allows us to identify the weight of both components in total inequality supposing neither a specific substitution degree among gases nor a particular weight to the different parts of the distribution.

(Place Figure 4 here)

[11] The $\beta$ parameter ranges from -1 to 9 by increments of 0.01 while, the $\gamma$ parameter ranges from -10 to 10 by increments of 0.5.

It is observed in the four graphs that the within-group inequality component predominated in most combinations of parameters. When all the countries received the same weight ($\gamma$ = 0), the between-group component predominated in the cases in which the substitution degree among contaminants was perfect or very high. Moreover, the share of total inequality that was explained by each inequality component seemed to be similar when it was admitted a lower substitution degree among gases.

## 5. Multivariate statistical polarization analysis

Having analysed the evolution of inequality in GHG emissions from a multivariate perspective, the polarization in the distribution of the four most important gases –$CO_2$, $CH_4$, $N_2O$ and F-gases–, is studied in the same time period, 1990-2011, using the measures detailed in Section 3. Table III shows the evolution of the multivariate polarization –using the $P_1$, $P_2$ and $P_3$ indices– for the four main pollutants over the period 1990-2011.

(Place Table III here)

The $\gamma$ parameter has been set to zero because it is the only assumption under which the polarization analysis make sense as the effect of the between-group inequality component was practically residual in the rest of combinations of parameters (see Figure 4). In addition, a perfect elasticity of substitution among gases ($\beta$ = -1) has been considered. Taking into consideration four groups, the $P_1$ index increased by 24 percent from 1990 to 1994, being this rate smaller from then on (around 19 percent). In the case $G$ = 8, the growth of the polarization was bigger –by 34 and 30 percent until and after the year 1994, respectively.

The $P_2$ and $P_3$ indices showed a slightly increasing pattern that remained constant throughout the period. Comparing both scenarios, while the evolution of the $P_2$ and $P_3$ indices was similar regardless of the number of groups considered, the $P_1$ index experienced an increase that was accentuated when a larger number of groups was admitted.

In this analysis, polarization in per capita GHG emissions increased from 1990 to 2011; however, in most studies devoted to measuring only the polarization in per capita $CO_2$ emissions, it was concluded the opposite trend (Duro and Teixidó-Figueras, 2014). The discrepancy in the results can be due mainly to the following fact. Unlike other works[12], in this study the groups of countries have been made using an endogenous-exogenous approach. Firstly, following the method proposed by Aghevli and Mehran (1981), we have determined endogenously the groups of countries taking as a reference the level of emissions released into the atmosphere by each country in the last year analysed. Secondly, we have considered the same grouping for all the years on account of keeping a consistent sample for the entire period and doing more feasible to establish environmental policies. Consequently, the maximum level of polarization is found in the year 2011, being also the one with the highest explanatory capacity of the inequality.

To complete the previous study of polarization, a sensitivity analysis of the evolution of polarization in $CO_2$, $CH_4$, $N_2O$ and F-gases emissions has been carried out, paying special attention to the degree of substitution among the preceding pollutants. Figure 5 shows the evolution of the three polarization indices –$P_1$, $P_2$ and $P_3$– from 1990 to 2011, assuming

[12] In the literature reviewed, the groups of countries are determined either exogenously or in an endogenous manner, varying the classification of countries from one year to another in the second case.

different values for the $\beta$ parameter and considering four and eight groups of countries, respectively.

(Place Figure 5 here)

The illustrations show that the $P_1$ and $P_3$ indices exhibited quite similar behaviour patterns. In both cases, the maximum level of polarization was reached in the year 2011 when the elasticity of substitution among pollutants was perfect ($\beta$ = -1). This result seems to be reasonable since the country grouping has been made taking as a reference that period. On the contrary, these indices reached the lowest value in 1990 when $\beta$ = 9 when the grouping was done around four groups. When the double number of poles was considered, the minimum took place in 2011, assuming a higher elasticity of substitution among pollutants ($\beta$ = 2).

With respect to the $P_2$ index of multivariate polarization, the maximum value was also recorded in 2011 for $\beta$ = -1, while the minimum was observed in the first year of study when the degree of substitution was low ($\beta$ = 9).

As for the evolution of the indices, a similar pattern for $P_1$ and $P_3$ indices was observed again. When $G$ = 4, polarization was reduced as the degree of substitution among gases decreased for the first two years of study. As the year 2011 was reached, the stabilization of polarization occurred at lower values of the $\beta$ parameter. For $G$ = 8, the polarization decreased from 1990 to 1994, regardless of the substitution degree among contaminants. For subsequent periods, the behaviour was similar to that observed for the other grouping of countries.

In relation to the evolution of the polarization displayed by $P_2$, the value of the index decreased in the first three years as the value of the $\beta$ parameter increased, irrespective of whether the country grouping was around 4 or 8 poles. In the rest of the years considered, the polarization was not stabilized until the degree of substitution among gases was smaller, unlike the behaviour observed for the $P_1$ and $P_3$ indices.

As the results vary depending on the value of the $\beta$ parameter, the principal implication of the previous choice is that the elasticity of substitution plays an important role in the variation of polarization in a manner that the greater substitution degree among gases, the higher polarization level. Thus, we can conclude that the $CO_2$-equivalent is a satisfactory measure in order to capture the polarization phenomenon.

## 6. Conclusions and Policy Implications

Although the per capita emissions are frequently more abundant in the rich countries, there are considerable exceptions. For example, some middle-income countries have similar per capita emissions levels to those of the wealthier economies. Given the existence of a wide variety of countries with different features and similar per capita emissions patterns, one-size-fits-all strategies are not likely to be favourable to the implementation of a stronger international environmental agreement.

In this sense, the multivariate polarization analysis presented in this paper provides a useful framework to understand the potential appearance of conflicts in the global distribution of per capita GHG emissions. In particular, this paper analyses the polarization in the global distribution of the principal GHGs from 1990 to 2011. For this purpose, both the generalised entropy measures proposed by Maasoumi (1986) and the multivariate polarization indices developed by Gigliariano and Mosler (2009) are used.

The multivariate polarization study gives the following outcomes. Comparing both scenarios, while the $P_2$ and $P_3$ indices showed a slightly increasing pattern that was similar regardless of the number of groups considered, the $P_1$ index experienced an increase that was accentuated when a larger number of groups was considered. In addition, it is observed that the three indices reached the maximum level of polarization in the year 2011 when the elasticity of substitution among pollutants was perfect ($\beta$ = -1). This result seems to be reasonable since the country grouping has been made taking as a reference that period.

In relation to environmental policies the following can be noted. Although climate change became a global matter in the 1990s, climate negotiations are surrounded by conflicts of interests between developed and developing countries. In this line, despite the fact that the Paris Agreement supposed a remarkable step towards the consideration of the different concerns of all Parties, there is still a long path ahead. Thus, in order to balance the two perspectives, political efforts should be made on the basis of the principle "common but differentiated responsibilities".

Regarding the probability of implementing international agreements, the fact that the $P_2$ and $P_3$ indices showed a slightly increasing pattern has to be perceived as positive in terms of advancing towards an international environmental negotiation for two reasons. Firstly, because the polarization degree was similar regardless of the number of groups considered and, secondly, because it suffered a little enlargement despite the fact that the country grouping has been made taking as a reference the year 2011.

It should also be noted that the divergence of the results based on the polarization index confirms that it is necessary to take into account different specifications for these indices in order to project a wide range of possible social and political conflicts and better understand climate negotiations.

In order to reduce the polarization in the global distribution of GHGs, this analysis suggests two policy directions. On the one hand, when the same weight to all countries is attributed and the substitution degree among gases is assumed to be perfect or very high, the attenuation must come from the convergence in the average emissions among the groups of countries given that the heterogeneity between groups is the most important component. On the other hand, for the rest of the combinations of the $\gamma$ and $\beta$ parameters, as it is observed a lowest degree of antagonism between groups, the contraction must come from the moderation of the intra-group cohesion.

As the multivariate inequality indices proposed by Maasoumi (1986) consider each country as a unit regardless of the size of its population, it would be very interesting to develop their corresponding weighted version to give a different weight to each country based on its share in the world population. In addition, the assessment of the evolution of the multivariate polarization for the entire period allowing that the groups of countries might be constituted in a different manner in each year will be a great complement to the presented analysis.

Notwithstanding, this analysis signifies one of the first works that study the evolution of GHG emissions considering different gases jointly. There are certain lines of research can be addressed in the future to expand this analysis. In this line, the availability of data about a greater number of GHGs, in a near future, will allow us to analyse the global polarization in emissions from a more realistic perspective which certainly will be useful tool for implementing policies to reduce the conflicts that can emerge for such polarization. In a similar way, the study of a longer time period will allow us to investigate the effects of the recent international agreements on this phenomenon.

**Acknowledgements**

The authors thank to Ministerio de Economía y Competitividad (Project ECO2016-76203-C2-1-PE) for the partial support of this work. In addition, this work is part of the Research Project APIE 1/2015-17: “New methods for the empirical analysis of financial markets” of the Santander Financial Institute (SANFI) of UCEIF Foundation resolved by the University of Cantabria and funded with sponsorship from Fundación Banco Santander.

## Appendix A

Endogenous classification of countries into four groups according to their level of per capita GHG emissions ($tCO_2e$) in 2011

**Group I [0.24 – 2.15)**

Albania, Armenia, Bangladesh, Bolivia, Brazil, Cambodia, Cameroon, Colombia, Congo (Democratic Republic of), Costa Rica, Dominican Republic, Ecuador, Egypt, El Salvador, Georgia, Ghana, Guatemala, Honduras, India, Indonesia, Ivory Coast, Kenya, Korea (Democratic People's Republic of), Kyrgyzstan, Moldova (Republic of), Morocco, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Panama, Peru, Philippines, Sri Lanka, Syria, Tajikistan, Tunisia, Vietnam, Yemen, Zambia, Zimbabwe.

**Group II [2.15 – 4.96)**

Algeria, Angola, Argentina, Azerbaijan, Bosnia and Herzegovina, Chile, Croatia, Cuba, Cyprus, France, Hungary, Iceland, Iraq, Jamaica, Jordan, Latvia, Lebanon, Lithuania, Macedonia (Republic of), Mexico, Mongolia, Portugal, Romania, Spain, Sweden, Switzerland, Thailand, Turkey, Uruguay, Uzbekistan, Venezuela.

**Group III [4.96 – 9.87)**

Austria, Belarus, Belgium, Bulgaria, China, Czech Republic, Denmark, Finland, Germany, Greece, Iran (Islamic Republic of), Ireland, Israel, Italy, Japan, Korea (Republic of), Libya, Malaysia, Netherlands, New Zealand, Norway, Poland, Russian Federation, Serbia, Singapore, Slovakia, Slovenia, South Africa, Ukraine, United Kingdom.

**Group IV [9.87 – 30.73]**

Australia, Bahrain, Brunei Darussalam, Canada, Estonia, Kazakhstan, Luxembourg, Oman, Qatar, Saudi Arabia, Trinidad and Tobago, Turkmenistan, United Arab Emirates, United States.

## Appendix B

Endogenous classification of countries into eight groups according to

their level of per capita GHG emissions ($tCO_2e$) in 2011

**Group I [0.24 – 1.25)**

Albania, Bangladesh, Cambodia, Cameroon, Congo (Democratic Republic of), El Salvador, Georgia, Ghana, Guatemala, Honduras, India, Ivory Coast, Kenya, Kyrgyzstan, Myanmar, Nepal, Nicaragua, Nigeria, Pakistan, Philippines, Sri Lanka, Tajikistan, Yemen, Zambia, Zimbabwe.

**Group II [1.25 – 2.73)**

Algeria, Angola, Armenia, Bolivia, Brazil, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, Indonesia, Jamaica, Jordan, Korea (Democratic People's Republic of), Moldova (Republic of), Morocco, Panama, Peru, Syria, Tunisia, Uruguay, Vietnam.

**Group III [2.73 – 4.22)**

Argentina, Azerbaijan, Chile, Croatia, France, Hungary, Iraq, Latvia, Lebanon, Lithuania, Macedonia (Republic of), Mexico, Portugal, Romania, Sweden, Switzerland, Thailand, Turkey, Uzbekistan.

**Group IV [4.22 – 5.61)**

Bosnia and Herzegovina, Bulgaria, China, Cyprus, Iceland, Italy, Mongolia, Serbia, Slovakia, South Africa, Spain, Ukraine, United Kingdom, Venezuela.

**Group V [5.61 – 7.75)**

Austria, Belarus, Denmark, Germany, Greece, Iran (Islamic Republic of), Ireland, Israel, Japan, Libya, Malaysia, New Zealand, Norway, Poland, Slovenia.

**Group VI [7.75 – 11.05)**

Belgium, Czech Republic, Estonia, Finland, Korea (Republic of), Netherlands, Russian Federation, Singapore, Turkmenistan.

**Group VII [11.05 – 17.12)**

Australia, Bahrain, Canada, Kazakhstan, Luxembourg, Saudi Arabia, United Arab Emirates, United States.

**Group VIII [17.12 – 30.73]**

Brunei Darussalam, Oman, Qatar, Trinidad and Tobago.

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**Figure 1.** Statistical polarization phenomenon

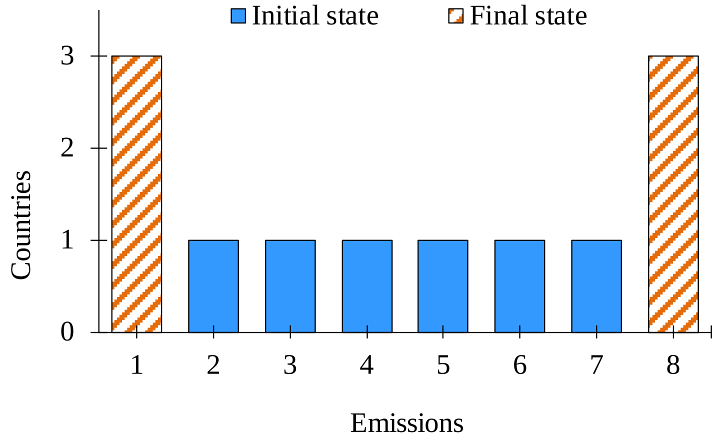


**Figure 2.** Endogenous classification of countries into four (top panel) and eight groups (bottom panel) according to their level of per capita GHG emissions in 2011

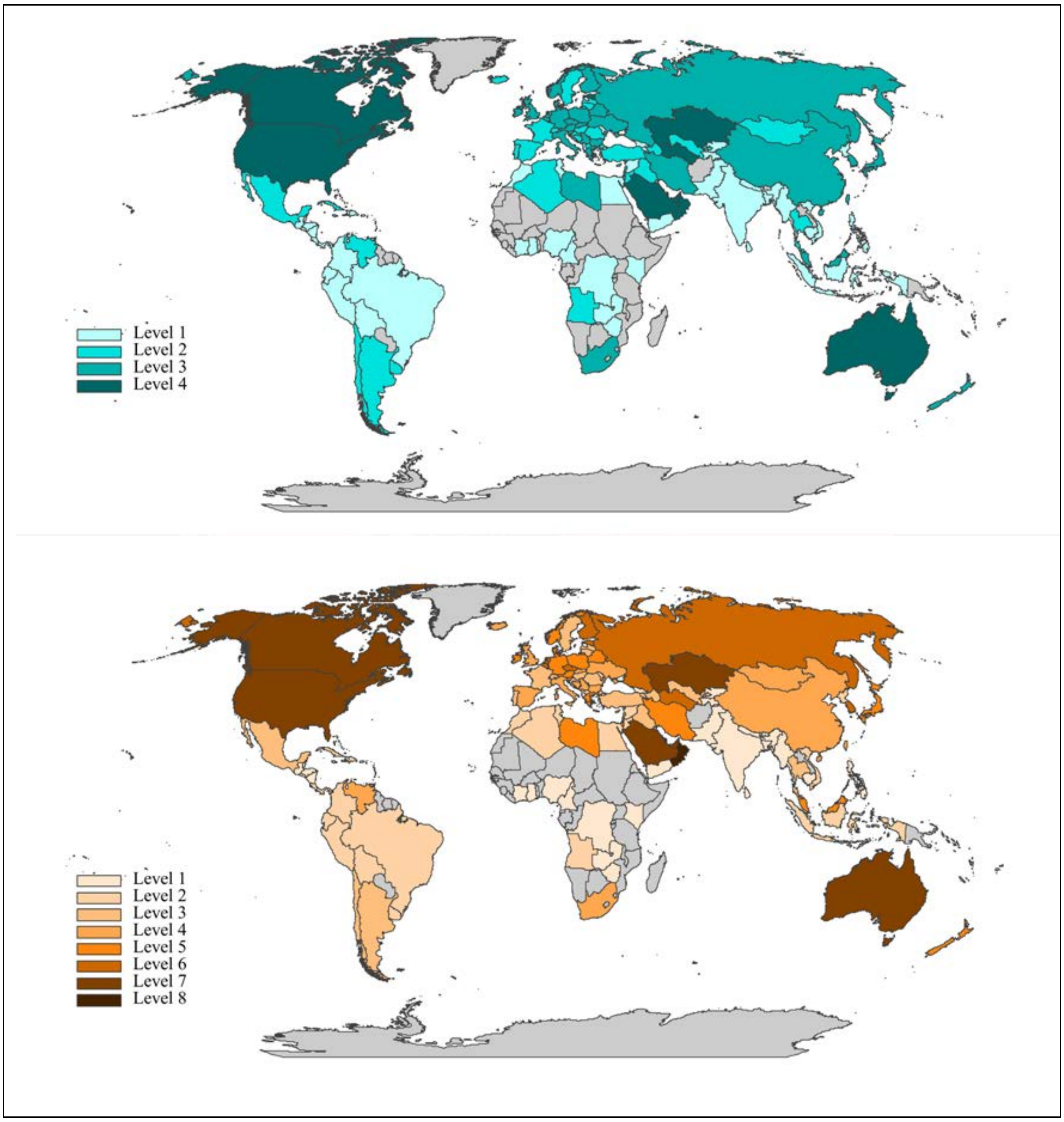


**Figure 3.** Decomposition of inequality in per capita GHG emissions by population sub-groups from 1990 to 2011 considering four (left panel) and eight groups (right panel)

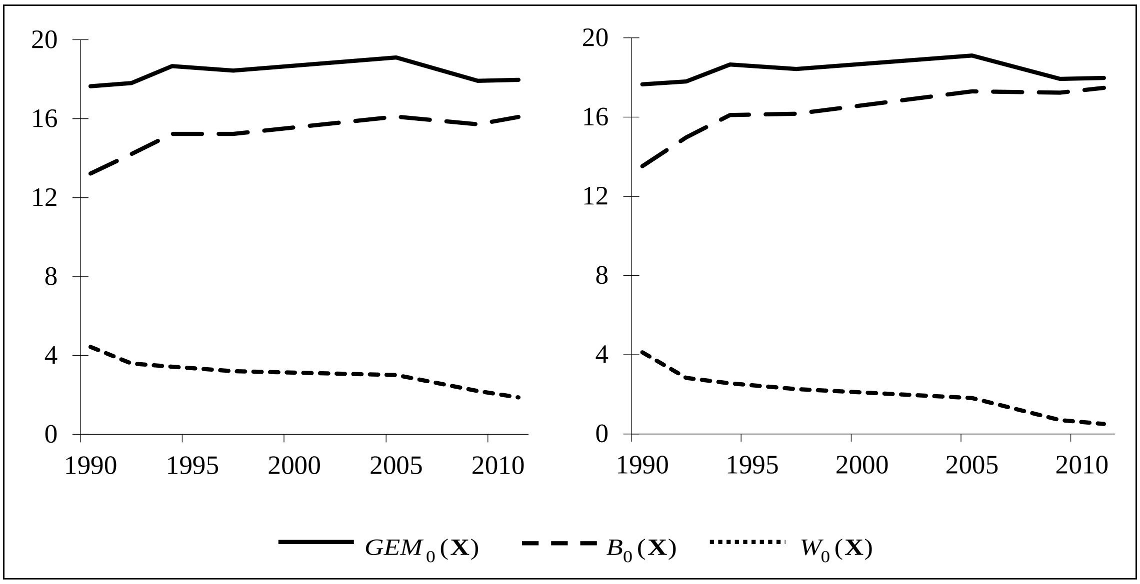
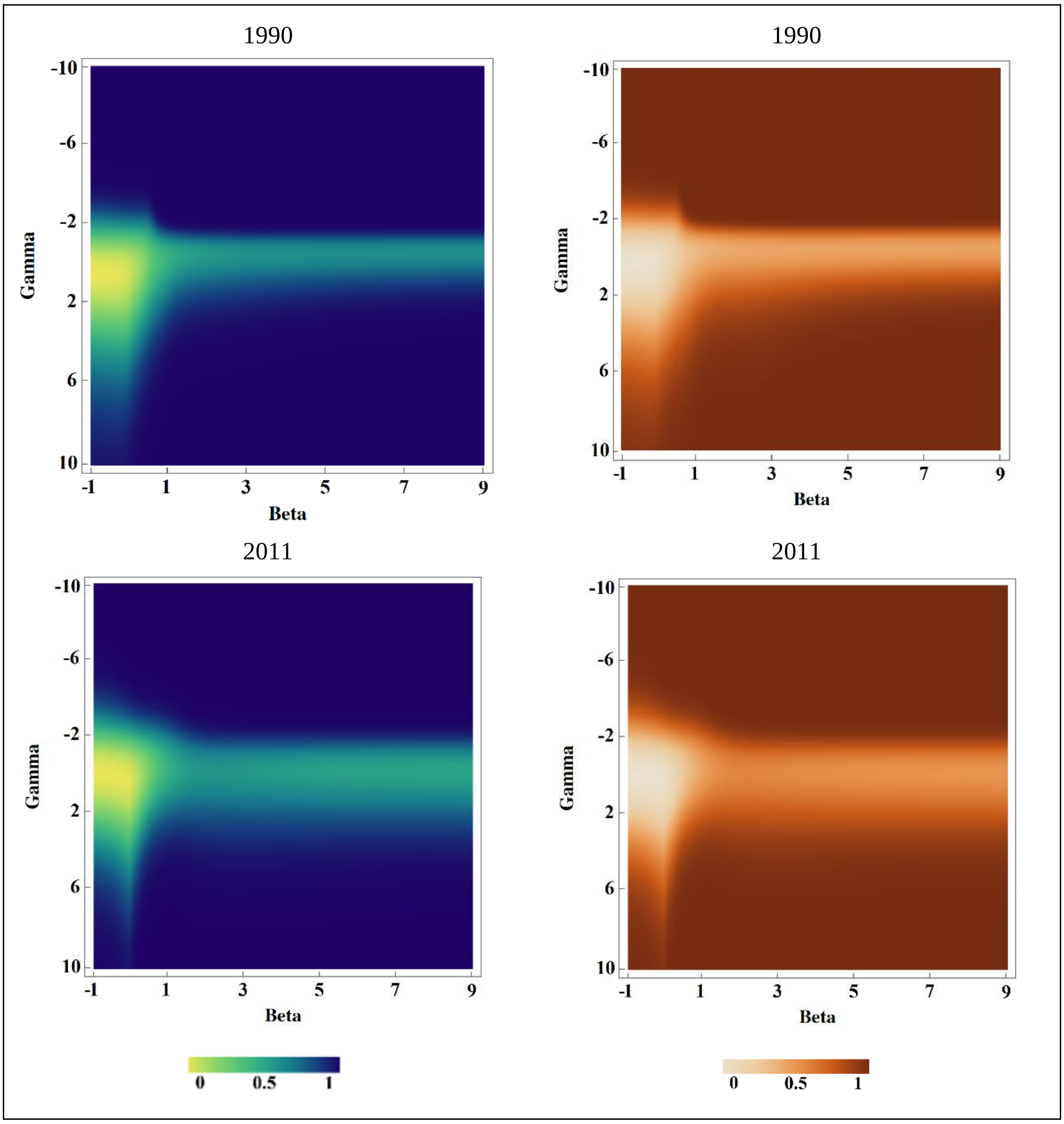


**Figure 4.** Contribution to inequality in per capita GHG emissions of the within-group inequality component in 1990 and 2011 considering four (left panel) and eight groups (right panel)




Note: The contribution is expressed in percentage.

**Figure 5.** Statistical polarization in per capita GHG emissions from 1990 to 2011 assuming different elasticities of substitution among gases and considering four (left panel) and eight groups (right panel)

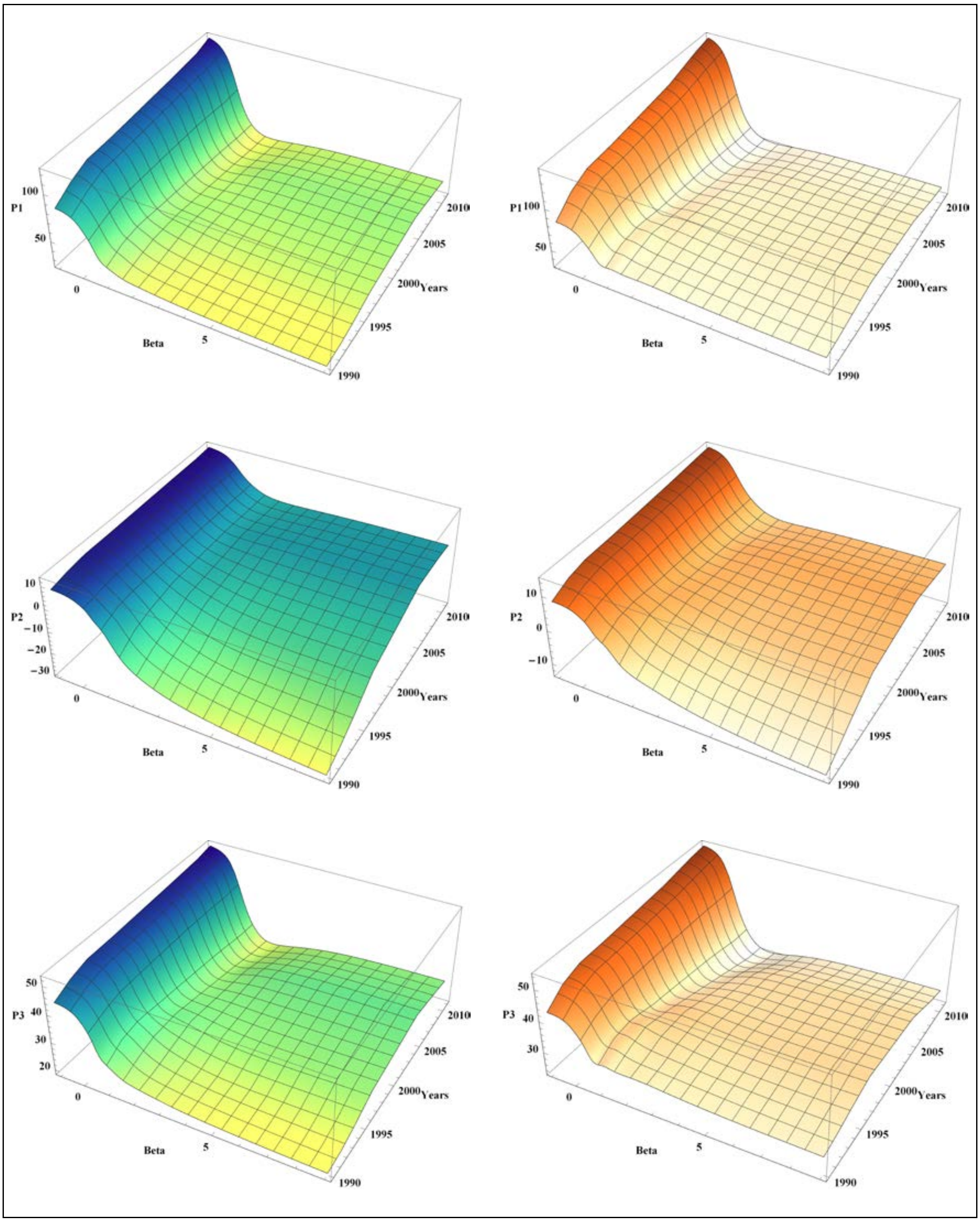


**Table I**. Elements of the between- and within-group inequality components

| **Gamma** | $\boldsymbol{f(y)}$ | $\boldsymbol{h(t;\bar{t})}$ | $\boldsymbol{w_g,\ g=1,\ldots,G}$ |
|---|---|---|---|
| $\gamma \neq 0,-1$ | $\frac{y}{\gamma(1+\gamma)}$ | $\left(\frac{t}{\bar{t}}\right)^{1+\gamma}-1$ | $\frac{N_g}{N}\left(\frac{\bar{s}^g}{\bar{s}}\right)^{1+\gamma}$ |
| $\gamma = -1$ | $y$ | $\log\left(\frac{t}{\bar{t}}\right)$ | $\frac{N_g}{N}$ |
| $\gamma = 0$ | $y$ | $\frac{t}{\bar{t}}\log\left(\frac{t}{\bar{t}}\right)$ | $\frac{N_g\bar{s}^g}{N\bar{s}}$ |

Source: Gigliariano and Mosler (2009).

**Table II.** Total inequality explained by the grouped distributions

| **Year** | ***G* = 4** | ***G* = 8** |
|---|---|---|
| 1990 | 75 | 77 |
| 1992 | 80 | 84 |
| 1994 | 82 | 86 |
| 1997 | 83 | 88 |
| 2005 | 84 | 91 |
| 2009 | 88 | 96 |
| 2011 | 90 | 97 |

Note: Inequality is expressed as percentage of the total value.

**Table III.** Statistical polarization in per capita GHG emissions from 1990 to 2011 considering four and eight groups

| | ***k* = 4** | | | ***k* = 8** | | |
|---|---|---|---|---|---|---|
| **Year** | $\boldsymbol{P_1}$ | $\boldsymbol{P_2}$ | $\boldsymbol{P_3}$ | $\boldsymbol{P_1}$ | $\boldsymbol{P_2}$ | $\boldsymbol{P_3}$ |
| 1990 | 0.8412 | 0.0807 | 0.4389 | 0.8327 | 0.0817 | 0.4254 |
| 1992 | 0.9601 | 0.0975 | 0.4693 | 1.0158 | 0.1057 | 0.4685 |
| 1994 | 1.0411 | 0.1083 | 0.4878 | 1.1153 | 0.1178 | 0.4886 |
| 1997 | 1.0582 | 0.1103 | 0.4915 | 1.1467 | 0.1209 | 0.4946 |
| 2005 | 1.1363 | 0.1202 | 0.5077 | 1.2750 | 0.1348 | 0.5170 |
| 2009 | 1.1831 | 0.1241 | 0.5169 | 1.4013 | 0.1438 | 0.5366 |
| 2011 | 1.2425 | 0.1304 | 0.5279 | 1.4476 | 0.1476 | 0.5432 |