Non-CO2 generating energy shares in the world: Cross-country differences and polarization[♦]

Abstract: The aim of this paper is to examine the spatial distribution of non-CO2 generating energy sources in the world for the period 1990-2009, paying special attention to the evolution of cross-country disparities. To this end, after carrying out a classical convergence analysis, a more thorough investigation of the entire distribution is presented by examining its external shape, the intra-distribution dynamics and the long-run equilibrium distribution. This analysis reveals the existence of a weak, rather insignificant, convergence process and that large cross-country differences are likely to persist in the long-run. Next, as polarization indicators are a proper way of appraising potential conflict in international environmental negotiations, we test whether, or not, the distribution dynamics concurs with the presence of polarization. Our results indicate that two poles can be clearly differentiated, one with high and other with low non-CO2 generating energy shares. In view of these findings, and to ensure a fair transition to a sustainable energy system, the paper calls for the development of an ambitious clean energy agenda, especially in countries with low non-CO2 generating energy shares.

Keywords: non-CO2 generating energy share; distribution dynamics approach; polarization.

[♦] We would like to thank two anonymous referees for their helpful comments and suggestions. The usual disclaimer applies.

1. Introduction

Public concern on global warming has notably increased during the last decades, to the point that this issue has become one of the most important challenges the world faces nowadays (e.g. VijayaVenkataRaman et al., 2012). This being so, it is evident that the use of non-CO2 generating energy sources (hereafter NCO2GES), commonly termed as 'clean energy',[1] should play, and is already playing, a central role in the current energy debate. It is obvious that the use of this kind of energy, by reducing greenhouse gas emissions and dependence on oil and other exhaustible resources, could significantly help to mitigate climate change impacts.

This, in turn, has given rise to an upsurge in the volume of empirical studies over the last few years, thus contributing to a much better understanding of the issue, which is at the basis of the United Nations Framework Convention on Climate Change (UNFCCC). Therefore, it is virtually impossible to acknowledge all researchers that have at some time dealt with this topic. In any case, it is convenient to make at least a passing reference to some of them just to notice that many questions have been examined, most of them so closely related to each other that it is really difficult to break them down into different groups. Some lines of research could be, however, pointed out: 1. Employment generation by the clean energy industry (e.g. Barrett and Hoerner, 2002; Kammen et al., 2004; Moreno and López, 2008; Wei et al., 2010; Tourkolias and Mirasgedis, 2011; Böhringer et al., 2013); 2. Guidelines for the promotion of this kind of energy (e.g. Haines et. al, 2007; Morris et al., 2012; Pollin, 2012); 3. Overview of clean energy technology options and its effectiveness (e.g. Brown, 2001; Amer and Daim, 2011; van

[1] Both terms, clean energy and non-CO2 generating energy sources, are used indistinctly in this paper.

Ruijven et al., 2012); 4. Economic assessment of NCO2GES (e.g. Borchers et al., 2007; Bollino, 2009; Scarpa and Willis, 2010); and 5. Future perspectives for the clean energy industry (Lund, 2010; Shafiullah et al., 2012).

Despite this there are still many pending and/or poorly studied questions, one of the most prominent being the study of the worldwide clean energy distribution. Taking for granted, as we will see in the next section, that the world average share of clean energy has increased in the last few decades, the main aim of this paper is to contribute to the literature by analyzing the evolution of cross-country differences in clean energy shares. Although, to the best of our knowledge, no previous study has dealt with this issue yet, we think is very relevant. Apart from the obvious fact that the promotion of this kind of energy is fully required for mitigating climate change, two additional elements have to be considered. First that the efforts made in implementing this type of energy differ substantially across countries, this meaning that global warming costs have not been equally shared across countries (Cooper, 2012). And second that because the negative environmental spillovers produced by countries with low clean energy shares, it may happen that the environmental benefits of those countries which already have a large portion of NCO2GES are not wholly reaped by them. Therefore, the catching-up of countries with lower clean energy shares would reduce this spillover problem and improve environmental conditions all over the world. As stated by Cooper (2012, p. S29) "climate change cannot be significantly slowed through actions by the rich countries alone", being necessary "the active participation of at least the largest emitters among the developing countries".[2]

[2] As Pretty (2013) suggests, the pathway to economic growth of developing countries does not have to be the same as those followed by the currently developed ones.

The paper also makes another contribution which is methodological in nature. Apart from the classical analysis of convergence, cross-country disparities in clean energy shares are also examined by means of the so-called distribution dynamics approach. It should be noticed that this latter approach has been recently applied to the analysis of CO_2 per capita emissions (Nguyen-Van, 2005; Ezcurra, 2007; Herrerias, 2012), and the world electricity consumption (Maza and Villaverde, 2008). There are, however, important features of this paper that should be emphasized. First, weighted instead of unweighted estimators are used to adjust for the different size of the units of analysis (countries). This is a remarkable factor because, as Herrerias indicates (2012, p. 10), "by weighting by population, some researchers have drawn different conclusions to those reached via unweighted analyses"; accordingly, we restrict ourselves to population weighted distributions. Second, the intra-distribution dynamics analysis is carried out by computing a new mobility index which allows us to quantify the mobility degree; this index exhibits better properties than the more conventional ones previously employed in environmental economics. Third, along with the distribution dynamics approach, this paper addresses the issue of polarization (Esteban et al., 1999). As Duro and Padilla (2008, 2013) recently stressed, the study of polarization offers additional insights on the distribution dynamics relative to the existence of different groups of countries (poles) and, in this way, about the potential existence of a catching-up process. Furthermore, the notion of polarization can be used to approximate potential conflicts in environmental negotiations.

The remainder of the paper is organized as follows. Section 2 describes data and stylized facts, among them the increase in the world average clean energy share over the last two decades. Both a conventional and a novel analysis of convergence on this type of energy is provided in Section 3. In Section 4 we go deeply into the study of cross-country disparities by examining the potential existence of polarization in the distribution. Finally, in Section 5 we summarize our main results and offer several policy suggestions.

2. Data and stylized facts

The information on clean energy shares used in this paper comes from the *World Development Indicators* databank published by the *World Bank*. According to it "clean energy includes noncarbohydrate energy that does not produce carbon dioxide when generated; it includes hydropower and nuclear, geothermal, and solar power, among others".[3] To be precise, information provided by the *World Bank* refers to 'clean energy share', namely the proportion that alternative and nuclear energy sources represents over total energy use. The choice of this databank lies on its reliability, as data consist on carefully constructed and fully comparable series between countries.

The sample in this paper consists of 114 countries over the period 1990-2009, the longer period for which data for such a large sample of countries are available. These countries represent more than 98% of the world GDP in 2009. The complete list of countries is shown in Appendix A.1.

[3] Under other definitions clean energy can also include cleaner fossil fuels such as clean coal or some low carbon energy sources.

To gain a first impression of our data, Table 1 shows the sample average of clean energy shares for every year in the sample. As can be seen, it goes from 5.11% in 1990 to 6.54% in 2009, which represents an annual rate of growth of 1.3%. Although with some fluctuations, the increase has been quite steady over the period under study. These figures could be taken as a signal that, to a certain extent, international agreements in the battle against climate change are being fruitful.

As indicated in the Introduction, however, this paper is focused on cross-country differences. Accordingly, Table 1 also depicts the sample countries with the three highest and lowest clean energy shares. This reflects remarkable differences across countries, some of them with values quite close (or even higher) than 100 while for others the use of NCO2GES is negligible. This fact is supported by the two maps in Fig. 1, displaying countries grouped by their clean energy shares for the initial (Fig. 1a) and final (Fig. 1b) years of the sample period. A quick glance at this figure shows that most European and American countries enjoy very high clean energy shares, whereas the use of this energy is much less extended in Africa and Oceania. Asian countries are somewhere in between. By comparing 1990 and 2009 we can also see that, although on the whole the continental distribution is fairly stable, some notable changes at country have taken place. In particular there are some countries (e.g. Belgium, Canada, Finland, Haiti, Nicaragua, Norway, Sweden, Uruguay) characterized by having a high relative use of NCO2GES in 1990 that have experienced a decrease in its use (or at least a lower increase than the world average). On the other side, there are also some countries (e.g. Albania, Armenia, China, Denmark, Georgia, Greece, Ireland, Mozambique, Romania) where the use of this type of energy has increased quite a lot.

Table 1 around here

Fig. 1 around here

3. An analysis of clean energy share convergence

After a cursory glance at the astonishing disparities in clean energy shares across countries and their evolution, this section is aimed at providing some insight into the existence or not of a clean energy share convergence process in the world over the period 1990-2009. We believe this is a crucial issue that needs to be addressed. The existence of a convergence process could make easier the achievement of clean energy agreements because it would favor the adoption of common objectives (as it is happening, for example, in the EU). As Padilla and Duro (2013) indicate, the evolution towards a distributive situation could make more likely to share positions on how to distribute mitigation burdens. Otherwise, it seems logical to expect that the negotiation process is going to be hard.

To assess potential signs of convergence in clean energy shares we use two complementary methodologies: the classical approach and the distribution dynamics approach. Before starting with our analysis, an important comment regarding data is mandatory. It is common practice in studies on convergence to give all units of analysis the same weight, therefore making no distinction according to their size (see, e.g, Ezcurra, 2007; Maza and Villaverde, 2008; Maza et al., 2010a). Doing this would imply that changes in clean energy shares for each country would have the same contribution to the convergence/divergence process independently of its size. As a result, it would happen, for instance, that China (the largest country in our sample in terms of population) would be clearly down-weighted while, on the contrary, Iceland (the smallest country) would be up-weighted. To solve this problem, our empirical analysis turns around the use of weighted estimators.

3.1. A classical convergence approach

First we apply the most conventional concept of convergence, namely that of σ-convergence.[4] This concept, entailing the reduction of the cross-sectional dispersion over time, is usually calculated by means of the most typical measure of dispersion: the (weighted, in our case) coefficient of variation. By normalizing its value to 100 in the initial year, Fig. 2 shows that clean energy share disparities, even with minor swings, have declined over the sample period. The coefficient of variation fell by 11% (an annual rate of 0.6%), this revealing the existence of a very weak process of convergence.

For the sake of robustness (Duro, 2012), we have also computed σ-convergence by employing other inequality indicators, specifically the well-known Atkinson (A(0.5) and A(1)), Gini (G) and Theil (T(0) and T(1)) measures. The results are also reported in Fig. 2. We observe that all the inequality indicators point to roughly the same evolution of cross-country disparities. The differences refer mainly to the speed of convergence. Although always weak, this is more intense according to the Theil coefficient $T(1)$

[4] The classical convergence approach is based on the seminal paper by Barro and Sala-i-Martin (1992). They proposed two measures of convergence, σ− and β-convergence. As the concept of β-convergence is less restrictive than the first one, we only show σ-convergence results; in fact, β-convergence is a necessary but not sufficient condition for σ-convergence.

(which fell by 17% in the period under study, corresponding to an annual convergence rate of 1.0%) and less significant according to the Gini index (7% and 0.4% respectively).

Fig. 2 around here

Some of these inequality measures, and in particular the Theil index, have the property of being additively decomposable. Taking advantage of this, we have decomposed clean energy shares into a direct product of three factors: 1. Clean energy intensity (CEI), defined as the ratio between clean energy and GDP; 2. Economic affluence (EA), defined as the ratio between GDP and population; 3. The inverse of the energy per capita (IEPC), defined as the inverse of the ratio between population and energy use.[5] Then, we have investigated the sources of the clean energy share disparities by measuring the contribution of each individual factor to the total inequality (for technical questions, see Padilla and Duro, 2013). As can be observed in Fig. 3, in 1990 the main factor behind the world disparities in NCO2GES shares was the economic affluence, followed at a distance by clean energy intensity, while the contribution of (the inverse of) energy per capita was even negative. Over the period, however, the contribution of the inequality in economic affluence has experienced a quite stable reduction, whereas the contribution of clean energy intensity has increased until 2000 and slightly decreased since then. Put it another way, the difference in the weight of clean energy per unit of GDP have picked up some of the role played by differences in GDP per

[5] Therefore, we have $\frac{CE}{TEU} = \frac{CE}{GDP} * \frac{GDP}{POP} * \frac{POP}{TEU} = CEI * EA * IEPC$, where CE denotes clean energy, TEU refers to total energy use, and POP is population.

capita levels. In consequence, in 2009 the relative importance of the former is even higher than that of the latter.

Fig. 3 around here

Additionally, we have also applied the traditional ‘between-within’ decomposition of the Theil index (see also Fig. 3). Considering that in the definition of clean energy proposed by the World Bank both renewable and nuclear energy are found mixed together, we have broken down our sample of countries into two groups: those in which nuclear energy is the main energy source among the NCO2GES, and those in which this place is occupied by renewable sources.[6] The results show that the between-group component explains less than 25% of total inequality in 1990 and only 18% in 2009. In other words, within-group heterogeneity is by large the main factor behind clean energy share disparities. The results thus indicate no substantially different behavior among countries depending on the source of non-CO2 generating energy that is predominant on them.

3.2. A distribution dynamics approach

Although offering important insights, the classical analysis of convergence presents several drawbacks (see, for example, Quah, 1996, 1997). In particular, it informs neither about changes in the external shape of the distribution nor about the fact that countries

---

[6] Although clean energy data provided by the World Bank are not split between nuclear and renewable sources, we proxied them by comparing the “electricity production from nuclear sources” and the “electricity production from renewable sources”.

may shift their relative position in the distribution over time. This section tries to overcome these two limitations.

3.2.1. External shape

First, we focus on the external shape of the clean energy share distribution and its evolution. To do that we estimate weighted univariate density functions, for which a key element is the selection of the proper smoothing parameter or bandwidth. The role of this parameter is to put less weight on observations that are further from the point being evaluated. Although either fixed or varying bandwidths can be used, a variable one is especially suitable when, as in our case, data sparseness is apparent. Varying the bandwidth from one point to another in the sample (a large bandwidth in regions of low density and a small one in regions with high density) allows us to adapt the estimator to the local density of data. The basic idea is that, by only varying the bandwidth along the support of the sample data, we can reduce the variance of the estimates in areas characterized by the presence of few observations (potential outliers), as well as the bias of the estimates in areas with many observations.

Accordingly, we compute a two-stage weighted adaptive kernel density estimator to minimize the sensitiveness of our estimations to the presence of potential outliers (for more details see Abramson, 1982; Goerlich Gisbert, 2003). For any variable Y this estimator is given by:

$$\hat{f}(y) = \sum_{i=1}^{n} \frac{w_i}{h\lambda_i} K\left(\frac{y - y_i}{h\lambda_i}\right) \tag{1}$$

where *K(.)* is a kernel function (Gaussian in this case), w_i are the weights associated to y_i ($\sum_{i=1}^{n} w_i = 1$) and $\lambda_i = \sqrt{g / \hat{f}(y_i)}$ are the bandwidth adjustment factors, g being the geometric average over all i of the pilot density estimate $\hat{f}(y)$ calculated using the fixed bandwidth h.[7] The value of h has been chosen following Silverman's rule of thumb (Silverman, 1986).

Fig. 4 around here

Before proceeding with the estimation, and as it is usual in order to facilitate comparisons and eliminate the effect of absolute changes in clean energy shares over time, country values are normalized to the world average (which is set equal to 100). As shown in Fig. 4, the results reveal that the shape of the distribution is roughly the same in 1990 as in 2009. It has a main mode below 50% of the average, being the range of the distribution quite large. In any case, some minor changes have taken place over the sample period. Perhaps the most noteworthy one is that there was a small bump in the distribution around 240% level in 1990 that has moved backwards in 2009. In terms of cross-country disparities, Fig. 4 does not reveal the existence of a notable process of convergence in NCO2GES, as both the ratio of extreme values and the concentration of the mass of probability around the mean have not changed significantly between 1990 and 2009. These results complement the previous ones, thus indicating that although

[7] This analysis was conducted by using STATA's akdensity command. Regarding weights, we used analytic weights (aweight), that is, weights that are inversely proportional to the variance of each observation; for example, the variance of the *i-th* observation is assumed to be σ^2/w_i, where w_i is the weight, namely the population of country *i*.

there have been advances in environmental protection by increasing the use of clean energy, more efforts are required to attain a distribution with all countries converging towards a mean that is increasing year by year.

3.2.2. Intra-distribution dynamics

Albeit informative, the previous analysis fails to clarify whether changes in the external shape of the distribution have been accompanied by changes in the relative position of countries within it (intra-distribution dynamics). Although it might seem so, this is not a minor question as changes within the distribution can provide useful information to infer some additional conclusions on convergence across economies. In order to gain some insight into this question, in this section we apply a discrete intra-distribution dynamics approach, the so-called Markov chain approach. The interest lies in that it allows us to quantify mobility within the distribution, preserving the imperative necessity of weighting data properly.

For it, let suppose that countries are classified into a finite number of exhaustive and mutually exclusive states according to their clean energy shares. Then, it is possible to define the distribution for these shares at times t and $t+s$, denoted by $v(t)$ and $v(t+s)$ and commonly referred as to initial and final distributions respectively. The link between both distributions is given by $v(t+s) = v(t) \cdot P(t, t+s)$, which defines the law of motion of the distribution between t and $t+s$. A key element in that relation is the operator $P(t, t+s)$, the so-called transition matrix between t and $t+s$ with generic elements $p_{ij}(t, t+s)$, as it maps the distribution from period t to period $t+s$. The interpretation of the transition matrix is particularly intuitive: its elements give the probability of moving from a state i to another j between t and $t+s$.

Provided the transition matrix is stationary, i.e. time-independent, so that it can be denoted as $P(s)$, the distribution is expected to converge to the so-called equilibrium distribution given by $\prod = \lim_{t\to\infty} P(s)^t$; this provides the direction in which the distribution is expected to evolve if current structural factors remain unchanged (Parzen, 1962; Durrett, 1999). As indicated by Bichenbach and Bode (2003), comparing the equilibrium (also called ergodic or limiting) distribution to the initial one can provide us information on the existence of a convergence or divergence process; specifically, convergence is reached when intra-distribution mobility leads to an equilibrium distribution with more probability mass at the middle states of the distribution.

To implement this approach several types of decisions must be made, starting with the definition of the states. As such, following Quah (1993) and, once again, taking 100 as the world average, the overall percentage of clean energy on total energy use at *t* is divided into five states of equal size representing countries with low (1), middle-low (2), middle (3), middle-high (4) and high (5) percentages of NCO2GES.[8] Another decision concerns the transition period length. In this case, and as is common in many

[8] Alternative methods for the discretization of the distribution include the proposal by Scott (1979), who defines an optimal bin width as a function of the sample size and the standard deviation, or the proposal by Magrini (1999) based on the minimization of an error measure. These methods of boundary selection, however, may lead to having a disproportionate number of states, some of them, as indicated by Bosker (2009), with very few observations.

applications on intra-distribution dynamics, we opted for estimating a five-year transition matrix (s = 5).[9]

Table 2 reports the number of observations and upper bounds of each state, the estimation of the five-year transition matrix, the initial and equilibrium distributions, and a measure of the speed of the system in approaching this limiting distribution called the asymptotic half-life (Shorrocks, 1978).[10] All estimations are based on maximum likelihood. Beginning with the transition matrix, it deserves to be highlighted that estimated values of transition probabilities along the main diagonal are relatively high, this being indicative of high persistence in countries' shares of NCO2GES. In addition, among countries which change their relative position within the distribution there is no clear predominance of either upward or downward movements. In view of these findings, we conclude that a process of convergence is virtually negligible. Moreover, a straightforward comparison of the equilibrium distribution with the initial one reveal that if current mobility patterns persist in the future, the long-term tendency will be that 24.9% of the sample countries will reach medium percentages of clean energy, while the equilibrium mass for the rest of states will slightly decrease or keep unchanged. Therefore changes in the dynamics of the distribution are not expected to be large, so that we can expect that country differences will persist in the future. Finally, the speed

[9] Whereas a one-year transition period, for example, would imply a very low degree of mobility and emerging patterns would be really difficult to detect, a longer transition period would lead, in the case of discrete-time estimation, to a noteworthy loss of information.

[10] Before proceeding with the estimation, we first tested for the existence of Markovian dependence using the χ^2−test proposed by Anderson and Goodman (1957). The results lead us to reject the null hypothesis of non-Markovian dependence at the 5% significant level (p−value=0.000), this implying we can properly compute a transition matrix.

of convergence equals to 11.257 (this value corresponds to about 11.257*5 $\approx$ 56 years), which indicates that the convergence process is expected to be very slow.

Table 2 around here

As indicated before, one reason that makes the Markov chain approach especially appealing is that scalar summary indices of mobility can be derived.[11] Here we resort to a novel mobility measure formulated by Maza et al. (2010b), this being the first time it is applied to the environmental field. This measure basically consists on an extension of Bartholomew's (1996) family of mobility measures that allows us to account for the different population size across countries in the sample, its expression being as follows:[12]

$$d(P) = \sum_i \sum_j \frac{1}{k_i} p_i p_{ij} d_{ij} \tag{2}$$

where p_i are population shares for clean energy states at *t*;[13] p_{ij} denote transition probabilities between *t* and *t+s*; $d_{ij} = \left| \bar{y}_j - \bar{y}_i \right|$ are absolute differences between the average percentage of clean energy between states at *t*; and, finally, k_i denotes the

[11] An excellent, comprehensive survey -and application- of these mobility indices can be seen in Duro (2013).

[12] For the sake of simplicity the equations of the paper contain no reference to time.

[13] In the original version of the mobility index proposed by Maza et al. (2010b) the element p_i is defined as the proportion of countries in each state at *t*. This definition implied weighting all transitions equally irrespective of countries' size.

largest value of each row in matrix *D* (distances matrix with generic elements d_{ij}). This mobility measure is perfectly bounded between 0 and 1, and its interpretation is straightforward: the closer its value to 1, the higher the mobility degree within the distribution.

As for the degree of mobility of each state separately, the aggregate measure in equation (2) can be decomposed into the so-called state-by-state measures, denoted by $d(P_i)$, that is:

$$d(P) = \sum_i p_i d(P_i) \tag{3}$$

where

$$d(P_i) = \sum_j \frac{1}{k_i} p_{ij} d_{ij} \tag{4}$$

Note that, as defined in equation (2), the essence of maximum mobility (i.e, $d(P)=1$) is that countries change their relative position within the distribution moving either upward or downward towards the more distanced clean energy state. As it is obvious, it is practically impossible for such situation to occur. Then and for the sake of interpretation, we have carried out several simulations to determine reasonable bounded values for $d(P)$ in order to properly discriminate between high, medium and low mobility degrees. On the basis of these simulations, Table 3 summarizes the criteria set for establishing a reasonable scale for mobility.

Table 3 around here

Bearing this in mind, we have first obtained the normalized distance matrix, that is, the matrix containing distances with all the elements divided by the factor k_i (see Table 4). A quick glance shows that normalized distances are appreciably shorter for the first three than for the last two states; this is because upper bounds in the first group of states are tighter than in the second one.

Table 4 around here

Table 5 reports the population shares and values for the state-by-state and aggregate indexes. The results provide a numeric support to the conclusions drawn in previous sections. According to the aggregate measure $d(P)$, of 0.043, mobility within the distribution can be qualified as low, this reinforcing the need of additional efforts to bring about a change to a more equal distribution of clean energy shares. In addition, a look into the state-by-state indices allows us to go more deeply into this result. As a feature of note the middle-high state of the distribution reaches the highest mobility (0.111). It is also worth noting that low and middle-low clean energy states display significantly low levels of mobility; in this case, despite some movements from these states to even non-contiguous states can be observed (see Table 2), low relative distances make the contribution of such transitions to total mobility to be almost negligible. Therefore, efforts to prevent climate change should be especially carried out by countries with a low use of clean energy sources, what could open up a debate about the urgent implementation of specific environmental policies and actions in them. Indeed, looking at the outcomes of recent climate actions it seems that policies devoted to foster diversification of primary energy sources have not been developed to a large scale in this group of countries.

Table 5 around here

4. An analysis of clean energy share polarization

The analysis carried out in Section 3 concluded that the process of cross-country convergence in clean energy shares, if it exists, is extremely weak. Additionally, it has been shown that high persistence in the relative position of countries is another key characteristic of the distribution. At this point, a question that comes to mind is whether this persistence has coexisted with changes in polarization levels. This is quite a relevant issue from an environmental point of view because if the distribution is highly polarized -this meaning that there exist various groups (poles) of countries with similar characteristics and important differences between groups-, the different groups could have conflicting interests and therefore hinder international environmental negotiations. In other words, negotiations to reach consensus among countries could be slower or even broken off at any time.

The study of polarization has undergone few but significant methodological advances since the early 1990s, among which those of Esteban and Ray (1994) and Esteban et al. (1999, 2007) –henceforth ER and EGR, respectively– have been undoubtedly the most widely used in empirical analysis. Traditionally, polarization analysis has been applied to income and/or productivity data (see, for instance, Duro, 2005; Ezcurra et al., 2007; Hierro and Maza, 2009), but more recently it has also found application to other contexts, such as migration (Hierro et al., 2012) and CO2 emissions (Duro and Padilla, 2008, 2013). The purpose of this section is to apply this methodology to NCO2GES data.

To that end, let us consider a clean energy share distribution defined by f, and a partition of it that defines *r* non-overlapping groups as intervals of clean energy shares $[z_{i-1}, z_i]$, with $i = 1, ..., r$. The ER (1994) measure of polarization, commonly referred to as the *simple polarization measure*, is defined as follows:

$$ER(\alpha) = \sum_{i=1}^{r} \sum_{j=1}^{r} p_i^{1+\alpha} p_j \left| \frac{y_i}{\mu} - \frac{y_j}{\mu} \right| \tag{5}$$

where, for the purpose of the present study, p_i and p_j denote population shares for country groups *i* and *j*, y_i and y_j are clean energy shares for groups *i* and *j*, μ is the world average clean energy share and, finally, α is a parameter measuring the degree of sensitivity of the index to polarization; this falls in the interval [1, 1.6].

As indicated, the computation of $ER(\alpha)$ requires the distribution to be previously pre-arranged in *r* groups or intervals and then replacing clean energy share data within a group by the group mean. This causes an obvious problem. The lesser is the number of groups, the bigger is the value of ER. This is because the ER index does not take into account that, as some intra-group dispersion is to be expected, the partition of the distribution causes a loss of distributional information and, for this reason, it provokes an error of approximation when computing polarization through the ER measure. To solve this drawback, EGR (1999) proposed an extended version of the ER polarization measure given by:

$$EGR(\alpha, \beta) = ER(\alpha) - \beta\varepsilon \tag{6}$$

As can be seen, this measure comprises two addends. First, the ER polarization measure. Second, the approximation error ε, its purpose being to capture the loss of information caused by grouping the distribution. This element is in turn modulated by a parameter $\beta \geq 0$ that reflects the sensitivity of the index to the groups' level of cohesion. .

The $EGR(\alpha, \beta)$ index has better properties than the $ER(\alpha)$ index. According to the *EGR* index definition, polarization in a distribution may increase either due to growing heterogeneity between groups derived from a larger distance in terms of clean energy shares between extreme groups (measured by $ER(\alpha)$), or because, as a result of more identified groups, homogeneity within groups is higher and intra-group dispersion is lower (so that ε decreases).

In order to define the specification error ε, it is necessary to return to the question of the grouping arrangement. Once the number of groups *r* is chosen exogenously, the following decision concerns the partition of the distribution and, therefore, the location of groups. But, which is the optimal partition of the distribution? EGR (1999) proposed to choose as optimal grouping the partition that minimizes the specification error and therefore intra-group dispersion. Taking the Gini coefficient as a benchmark measure of inequality, we can define the specification error as $\varepsilon = G - G_s$, where G and G_s are the Gini coefficients of the original (i.e. ungrouped) and the optimally grouped distribution, respectively. Therefore, the final expression for the *EGR* polarization measure is as follows:

$$EGR(\alpha,\beta)=\sum_{i=1}^{r}\sum_{j=1}^{r}p_i^{1+\alpha}p_j\left|\frac{y_i}{\mu}-\frac{y_j}{\mu}\right|-\beta(G-G_s) \qquad (7)$$

with groups' means and population shares defined for the optimal partition of the distribution.

After the polarization measure has been defined, some remarks are compulsory before proceeding to its computation. The first one regards to the number of groups considered. As previously mentioned, one of the main goals of this section is to assess the likelihood of conflict in environmental negotiations. According to Esteban and Ray (1999), it depends, among other things, on the number of poles. For this reason, we consider the cases of 2, 3 and 4 groups.[14] The second remark refers to the lack of consensus on the value of α; for robustness reasons and following the most common choice on this issue, here we have chosen values of 1, 1.3 and 1.6. The third and last one is related to the value of β; in this case there is general agreement that this value must be close to 1, so that we have chosen $\beta=1$.

Table 6 reports the results obtained. As can be noted, although with some ups and downs, a decrease in polarization has occurred over the sample period, irrespective of the number of groups and the value of α. Additionally, the reduction in the level of

[14] Empirical evidence has revealed that there is not significant increase in the explanatory power when more than 4 groups are taken into account.

polarization is quite similar, going from 11% for the case of four groups and $\alpha = 1$ to 16.7% for the case of two groups and $\alpha = 1.6$. Regarding the evolution of polarization, however, the three-group case is quite singular as it shows a notable increase in the level of polarization over the sample period, albeit vanishing at the end.

Table 6 around here

Table 7 provides further insights into the role played by polarization between groups and homogeneity between them on the polarization trend. These results show that decreasing bipolarization has been almost due to a fall in polarization between groups. Indeed, if we take a look at the specification error, intra-group dispersion, despite some swings, has slightly declined (0.6%), this entailing groups becoming internally more homogeneous and therefore increasing, for this side, the degree of polarization. On the contrary, when three and four groups are considered we can observe that the intra-grouped dispersion increased in a non negligible way along the sample period (3.7% and 6.8%, respectively), so that in this case the specification error also contributed, although to a lesser extent than polarization between groups, to the reduction of polarization.

Table 7 around here

Furthermore, Table 8 reports both population and clean energy shares. As can be observed there were not significant changes in population shares over the sample period, but only a small transfer of population from the first to the rest of groups. It is worth mentioning, anyway, the three-group case, as there was a very significant transfer of population from the second to the first group in the mid 1990s, but the same movement in the opposite direction took place in the mid 2000s. China is behind this fact, which explains the increase in the level of tripolarization mentioned above. From the point of view of clean energy shares, another salient feature is that distances between groups' means have progressively diminished over the period, albeit at a slow pace. This allows us to explain, on the one hand, the falling levels of polarization between groups obtained in Table 6 and, on the other, the existence of a weak convergence process in NCO2GES.

Table 8 around here

At this point, and to properly link polarization to the notion of conflict, we should ask an important question: what level of polarization better conforms to reality? To answer it, and following the suggestion made by Duro and Padilla (2008), a useful criterion is based on the value of *EGR*. This being so, we can assert that bipolarization seems to be the best way to describe the clean energy share distribution, as the *EGR* always takes the highest value in this case. This statement is also supported by the fact that the split of the distribution into two groups of countries contributes to explaining (ratio G_s/G) almost 80% of the cross-country differences, which is quite a significant percentage. As it is obvious, the consideration of three or four groups increases this percentage (to almost 90 and 95% respectively), but the value of the *EGR* index indicates that the smaller aggregation error does not compensate the smaller heterogeneity between groups. In this matter, bipolarization seems to be the main feature of the world clean energy share distribution. As a good picture of reality, Appendix A.2 reports the list of countries that make up these two groups for the final year (2009) of our sample.

With all these considerations in mind, what could be said about conflict in environmental negotiations? Here we have mixed results. On the one hand, that negotiations will continue being really difficult because of the existence of strong bipolarization.[15] As Esteban and Ray (1999, p. 402) indicate, "there is a two-point symmetric distribution of population which globally maximizes conflict". Although this is not the case, as the two groups are not equally populated, it is true that differences between them are quite remarkable.[16] On the other hand, however, the world is moving towards a weaker bipolarization degree, which in return may reduce conflict potential over time. There are two other facts supporting this belief: first, that the decrease in polarization rested on a fall in polarization between groups; second, that distances between groups were even higher two decades ago than they are today. Additionally, it is important to note that the reduction in polarization is especially intense from 1997 onwards, coinciding with climate change initiatives taken under the UNFCCC and the initial adoption of the Kyoto Protocol.

5. Concluding remarks and policy implications

The promotion of non-CO2 generating energy sources constitutes the best strategy to cope with global warming, one of the most important challenges mankind faces not only nowadays but, most probably, also in the future. Therefore, unveiling the main

[15] To this respect, Montini (2011) highlights that one of the major problems surrounding the present climate change regime is the challenge of fragmentation of negotiations.

[16] In the last year of our sample, for example, the group characterized by low clean energy share reached only 42% of the world average, while the high clean energy share group reached 234% of the world average.

characteristics of the world clean energy share distribution seems to be of paramount importance. To the best of our knowledge, however, this topic has not been conveniently addressed in the literature. By means of using both traditional and novel approaches, this is, precisely, the gap we have tried to fill in this paper for a sample of 114 countries over the period 1990-2009. After briefly describing data, the following conclusions emerge from the analysis:

First, classical analysis of σ-convergence has shown that, whatever the inequality measure, cross-country disparities in clean energy shares have only slightly decreased over time; to be precise, the annual speed of convergence was around 0.6%. Put it in another way, some efforts in promoting NCO2GES have not led to a noticeable reduction in cross-country disparities. Regarding the contribution of different factors to total inequality, per capita GDP disparities play a quite remarkable role, although their contribution decreased over time. It seems, therefore, that it is necessary to achieve a strong correlation between GDP per capita levels and the efforts required to the different countries in order to increase the perceived fairness of environmental agreements.

Second, the distribution dynamics approach has revealed that the shape of the distribution did not changed significantly over time. In addition, it has been found that: 1. Persistence, or reduced mobility, is the main trait of the distribution; 2. The low mobility degree observed has not contributed to convergence, as there are countries with initially high (low) levels of NCO2GES that have improved (worsened) their relative positions over the time span; 3. Large cross-country disparities are expected to persist in the foreseeable future.

Finally, the paper has examined the polarization degree in the distribution. This is an interesting issue because measures of polarization appraise, in a better way than inequality indices, the potential conflict, and this is, without any doubt, a timely issue. It will be mandatory in the next coming years to achieve agreements between countries that tend to form groups in order to increase their negotiation power in designing climate change policies. The paper found that a noticeable bipolarization is the predominant feature; this notwithstanding, the bipolarization degree declined over time. In other words, the catching-up of countries with lower clean energy shares suggested by Cooper (2012) has in fact taken place, although at a degree far from the required one. This reduction in bipolarization was just the consequence of the decreasing polarization between groups, as the internal cohesion within groups slightly increased over the sample period. According to these findings, we can assert that the distribution of NCO2GES conveys a better situation for facilitating international agreements on mitigation policies in 2009 than in 1990, this being specially true since 1997 (Kyoto Protocol). Differences between groups are, however, still notable, so it is foreseeable that there will be high tension in the negotiations between groups of countries with opposing interests. This might be so especially because drastic reductions in greenhouse-gas emissions are and will be required to stabilize atmospheric gases at reasonable levels.

Now, bearing in mind that the use of NCO2GES to face climate change is inevitable and that climate change cannot be significantly mitigated through country-specific actions (see e.g. Golombek and Hoel, 2011), how can we interpret our results? Our opinion is that they give rise to a word of warning. Firstly, because they clearly show that the world is not committed to a well-orchestrated strategy in seeking a global shift to a green economy in which clean energy shares account for a high portion of the total energy used in every country.[17] Secondly because, although we are well aware that our findings cannot be taken as a face-value long term forecast of the world clean energy share distribution, they suggest that the extent of disparities and the relative position of the countries in the distribution will most probably persist in the future. Therefore, if we agree that is necessary to keep a convergence process and, if possible, speed up the pace of rising clean energy share in the world in order to mitigate climate change, the paper calls for a major impulse to NCO2GES promotion, mostly in those countries where efforts up to now have been quite weak and/or fruitless.

Therefore, it seems clear that a change of direction is needed, and this is not an easy task at all. Although it is true that the use of NCO2GES have gained legitimacy in the political arena, yet perception of clean energy as just a 'complementary' source of energy still remains. This is even more so because of the recent Japanese nuclear disaster that has put more pressure on countries that have relied up to now on nuclear power as an alternative to non-clean energy sources. Assuming this is not enough in itself, it happens that in times of constrained public finances there might be even more political reluctance to confront the energy dilemma in a more definitive fashion. Under this adverse scenario, what should be really important for all of us is that conventional economic growth (namely, GDP and consumption growth) is no longer the primary political goal, giving way to the use of technologies that promote "clean growth" and well-being gain (Pretty, 2013). In other words, politicians should be aware that the costs

[17] For an excellent paper studying the conditions to achieve an unilateral climate action see Bosetti and De Cian (2013).

of NCO2GES are low compared to the benefits, and that the overall (monetary and non-monetary) costs to society of non-clean energy sources are high. If so, policymakers will be convinced of the need to search for new formulas in favor of clean energy, among which these have already attracted some attention. First, the introduction of a zero tariff for green electricity to make fossil fuel energy more expensive in relative terms; this policy was implemented in The Netherlands in 1996.[18] Second, the existence of a more stable legal framework to reduce market uncertainties and to generate confidence among market actors. Third, the promotion of clean energy-based technologies; South Korea is a good example with technologies such as space solar power and polymer electrolyte fuel cells. Fourth, the removal of administrative bottlenecks. Fifth, the implementation of eco-compensation schemes; China is a clear illustration of this sort of tool. And finally, the seek for a better climate change governance regime commanded by an international institution that promotes effective coordination of the existing multilateral agreements and related initiatives (Montini, 2011).

[18] An alternative option could be to increase taxes on CO_2 emissions. But, according to Sinn (2007, 2008) arguments, this would lead to the well-known Green paradox. For a revision of this paradox see Spinesi (2012).

Appendix A.1: List of countries

Albania	Georgia	New Zealand
Algeria	Germany	Nicaragua
Angola	Ghana	Nigeria
Argentina	Greece	Norway
Armenia	Guatemala	Pakistan
Australia	Haiti	Panama
Austria	Honduras	Paraguay
Azerbaijan	Hungary	Peru
Bangladesh	Iceland	Philippines
Belarus	India	Poland
Belgium	Indonesia	Portugal
Bolivia	Iran, Islamic Rep.	Romania
Bosnia and Herzegovina	Iraq	Russian Federation
Brazil	Ireland	Serbia
Bulgaria	Israel	Slovak Republic
Cameroon	Italy	Slovenia
Canada	Jamaica	South Africa
Chile	Japan	Spain
China	Jordan	Sri Lanka
Colombia	Kazakhstan	Sudan
Congo, Dem. Rep.	Kenya	Sweden
Congo, Rep.	Korea, Dem. Rep.	Switzerland
Costa Rica	Korea, Rep.	Syrian Arab Republic
Cote d'Ivoire	Kyrgyz Republic	Tajikistan
Croatia	Latvia	Tanzania
Cuba	Lebanon	Thailand
Cyprus	Lithuania	Togo
Czech Republic	Luxembourg	Tunisia
Denmark	Macedonia, FYR	Turkey
Dominican Republic	Malaysia	Ukraine
Ecuador	Mexico	United Kingdom
Egypt, Arab Rep.	Moldova	United States
El Salvador	Morocco	Uruguay
Estonia	Mozambique	Uzbekistan
Ethiopia	Myanmar	Venezuela, RB
Finland	Namibia	Vietnam
France	Nepal	Zambia
Gabon	Netherlands	Zimbabwe

Appendix A.2: Country clusters

Low clean energy share	High clean energy share
Algeria	Albania
Angola	Argentina
Australia	Armenia
Azerbaijan	Austria
Bangladesh	Belgium
Belarus	Bosnia and Herzegovina
Bolivia	Brazil
Cameroon	Bulgaria
China	Canada
Congo, Dem. Rep.	Chile
Congo, Rep.	Colombia
Cote d'Ivoire	Costa Rica
Cuba	Croatia
Cyprus	Czech Republic
Denmark	Ecuador
Dominican Republic	El Salvador
Egypt, Arab Rep.	Finland
Estonia	France
Ethiopia	Georgia
Gabon	Germany
Ghana	Hungary
Greece	Iceland
Guatemala	Indonesia
Haiti	Japan
Honduras	Kenya
India	Korea, Rep.
Iran, Islamic Rep.	Kyrgyz Republic
Iraq	Latvia
Ireland	Lithuania
Israel	Mozambique
Italy	Namibia
Jamaica	New Zealand
Jordan	Nicaragua
Kazakhstan	Norway
Korea, Dem. Rep.	Panama
Lebanon	Paraguay
Luxembourg	Peru
Macedonia, FYR	Philippines
Malaysia	Romania
Mexico	Russian Federation
Moldova	Slovak Republic
Morocco	Slovenia
Myanmar	Spain
Nepal	Sweden
Netherlands	Switzerland
Nigeria	Tajikistan
Pakistan	Ukraine
Poland	United Kingdom
Portugal	United States
Serbia	Uruguay
South Africa	Venezuela, RB
Sri Lanka	Zambia
Sudan	
Syrian Arab Republic	
Tanzania	
Thailand	
Togo	
Tunisia	
Turkey	
Uzbekistan	
Vietnam	
Zimbabwe	

References:

Abramson IS (1982) On bandwidth variation in kernel estimates: A square root law. Ann Stat 10(4):1217-1223.

Amer M, Daim TU (2011) Selection of renewable energy technologies for a developing county: A case of Pakistan. Energy Sustain Dev 15(4):420-435.

Anderson TW, Goodman LS (1957) Statistical inference about Markov chains. Ann Math Statist 28:89-109.

Barrett JP, Hoerner JA (2002) Clean energy and jobs: A comprehensive approach to climate change and energy policy. Economic Policy Institute, Washington D.C.

Barro R, Sala-i-Martin X (1992) Convergence. J Polit Econ 100(21):223-251.

Bartholomew DJ (1996) The statistical approach to social measurement. Academic Press, London.

Bichenbach F, Bode E (2003) Evaluating the Markov property in studies of economic convergence. Int Regional Sci Rev 26(3):363-392.

Böhringer C, Keller A, van der Werf E (2013) Are green hopes too rosy? Employment and welfare impacts of renewable energy promotion. Energ Econ 36:277-285.

Bollino CA (2009) The Willingness to Pay for Renewable Energy Sources: The Case of Italy with Socio-demographic Determinants. Energ J 30(2):81-96.

Borchers AM, Duke JM, Parsons GR (2007) Does willingness to pay for green energy differ by source? Energ Policy 35(6):3327-3334.

Bosetti V, De Cian E (2013) A goof opening: The key to make the most of unilateral climate action. Environ Resour Econ, doi: 10.1007/s10640-013-9643-1.

Bosker M (2009) The spatial evolution of regional GDP disparities in the old and the new Europe. Pap Reg Sci 88:3–27.

Brown MA (2001) Market failures and barriers as a basis for clean energy policies. Energ Policy 29(14): 1197-1207.

Cooper RN (2012) Financing for climate change. Energ Econ 34(S1):S29-S33.

Duro JA (2005) Another look to income polarization across countries. J Policy Model 27:1001−1007.

Duro JA (2012) On the automatic application of inequality indexes in the analysis of the international distribution of environmental indicators. Ecol Econ 76:1-7.

Duro JA (2013) International mobility in carbon dioxide emissions. Energ Policy 55:208-216.

Duro JA, Padilla E (2008) Analysis of the international distribution of per capita CO_2 emissions using the polarization concept. Energ Policy 36:456-466.

Duro JA, Padilla E (2013) Cross-country polarization in CO2 emissions per capita in the European Union: changes and explanatory factors. Environ Resour Econ 54(4):571-591.

Durrett R (1999) Essentials of Stochastic Processes. Springer Verlag.

Esteban JM, Gradín C, Ray D (1999) Extensions of a Measure of Polarization with an Application to the Income Distribution of Five OECD Countries. Luxembourg Income Study Working Paper Series 218, Maxwell School of Citizenship and Public Affairs, Syracuse University, Syracuse, New York.

Esteban JM, Gradín C, Ray D (2007) An extension of a measure of polarization, with an application to the income distributions of five OECD countries. J Econ Inequal 5:1−19.

Esteban JM, Ray D (1994) On the measurement of polarization. Econometrica 62:819−852.

Esteban JM, Ray D (1999) Conflict and distribution. J Econ Theory 87:379-415.

Ezcurra R (2007) Is there cross-country convergence in carbon dioxide emissions? Energ Policy 35:1363-1372.

Ezcurra R, Pascual P, Rapún M (2007) Spatial disparities in the European Union: An analysis of regional polarization. Ann Regional Sci 41:401−429.

Goerlich Gisbert FJ (2003) Weighted samples, kernel density estimators and convergence. Empir Econ 28:335-351.

Golombek R, Hoel M (2011) International cooperation on climate-friendly technologies. Environ Resour Econ 49:473-490.

Haines A, Smith KR, Anderson D et al (2007) Policies for accelerating access to clean energy, improving health, advancing development, and mitigating climate change. Lancet 270(9594):1264-1281.

Herrerias MJ (2012) CO2 weighted convergence across the EU-25 countries (1920-2007). Appl Energ 92:9-16.

Hierro M, Maza A (2009) Structural shifts in the dynamics of the European income distribution. Econ Model 26(3):733−739.

Hierro M, Maza A, Villaverde J (2012) Explaining polarisation in the EU27's international migration distribution. Tijdschr Econ Soc Ge 103(4):396-411.

Kammen DM, Kapadia K, Fripp M (2004) Putting renewables to work: How many jobs can the clean energy industry generate? RAEL Report, University of California, Berkeley.

Lund PD (2010) Fast market penetration of energy technologies in retrospect with application to clean energy futures. Appl Energ 87(11):3575-3583.

Magrini S (1999) The evolution of disparities among the regions of the European Union. Reg Sci Urban Econ 29:257-281.

Maza A, Hierro M, Villaverde J (2010a) Renewable electricity consumption in the EU-27: Are cross-country differences diminishing? Renew Energ 35(9):2094-2101

Maza A, Hierro M, Villaverde J (2010b) Measuring intra-distribution dynamics: An application of different approaches to the European regions. Ann Regional Sci 45(2):313−329.

Maza A, Villaverde J (2008) The world per capita electricity consumption distribution: Signs of convergence? Energ Policy 36(11):4255-4261.

Montini M (2011) Reshaping climate governance for post-2012. Eur J Legal Stud 4(1):7-24.

Moreno B, López AJ (2008) The effect of renewable energy on employment. The case of Asturias (Spain). Renew Sust Energ Rev 12(3):732-751.

Morris AC, Nivola PS, Schultze CL (2012) Clean Energy: Revisiting the challenges of industrial policy. Energ Econ 34(S1):S34-S42.

Nguyen-Van P (2005) Distribution dynamics of CO2 emissions. Environ Resour Econ 32(4):495-508.

Padilla E, Duro A (2013) Explanatory factors of CO2 per capita emission inequality in the European Union. Energ Policy 62:1320-1328.

Parzen E (1962) Stochastic Processes. Holden-Day, San Francisco.

Pollin R (2012) Public policy, community ownership and clean energy. Camb J Reg Econ Soc 5(3):339-356.

Pretty J (2013) The consumption of a finite planet: well-being, convergence, divergence and the nascent green economy. Environ Resour Econ, doi: 10.1007/s10640-013-9680-9.

Quah D (1993) Empirical cross-section dynamics in economic growth. Eur Econ Rev 37:426-434.

Quah D (1996) Regional convergence clusters in Europe. Eur Econ Rev 40(3-5):951-958.

Quah D (1997) Empirics for growth and distribution: Stratification, polarisation, and convergence clubs. J Econ Growth 2:27-59.

Scarpa R, Willis K (2010) Willingness-to-pay for renewable energy: Primary and discretionary choice of British households' for micro-generation technologies. Energ Econ 32(1):129-136.

Scott DW (1979) Optimal and data-based histograms. Biometrika 66:605-610.

Shafiullah GM, Amanullah MTO, Shawkat Ali ABM et al (2012) Prospects of renewable energy – a feasibility study in the Australian context. Renew Energ 39(1):183-197.

Shorrocks AF (1978) The measurement of mobility. Econometrica 46:1013-1024.

Silverman BW (1986) Density estimation for statistics and data analysis. Chapman and Hall, London.

Sinn WH (2007) Pareto optimality in the extraction of fossil fuels and the greenhouse effect. CESIFO Working Paper n. 2083.

Sinn WH (2008) Public policies against global warming: a supply side approach. Int Tax Public Finan 15(4):360-394.

Spinesi L (2012) Global warming and endogenous technological change: Revisiting the green paradox. Environ Resour Econ 51:545-559.

Tourkolias C, Mirasgedis S (2011) Quantification and monetization of employment benefits associated with renewable energy technologies in Greece. Renew Sust Energ Rev 15(6):2876-2886.

van Ruijven BJ, van Vuuren DP, van Vliet J et al (2012) Implications of greenhouse gas emission mitigation scenarios for the main Asian regions. Energ Econ 34(S3):S459-S469.

VijayaVenkataRaman S, Iniyan S, Goic R (2012) A review of climate change, mitigation and adaptation. Renew Sust Energ Rev 16(1):878-897.

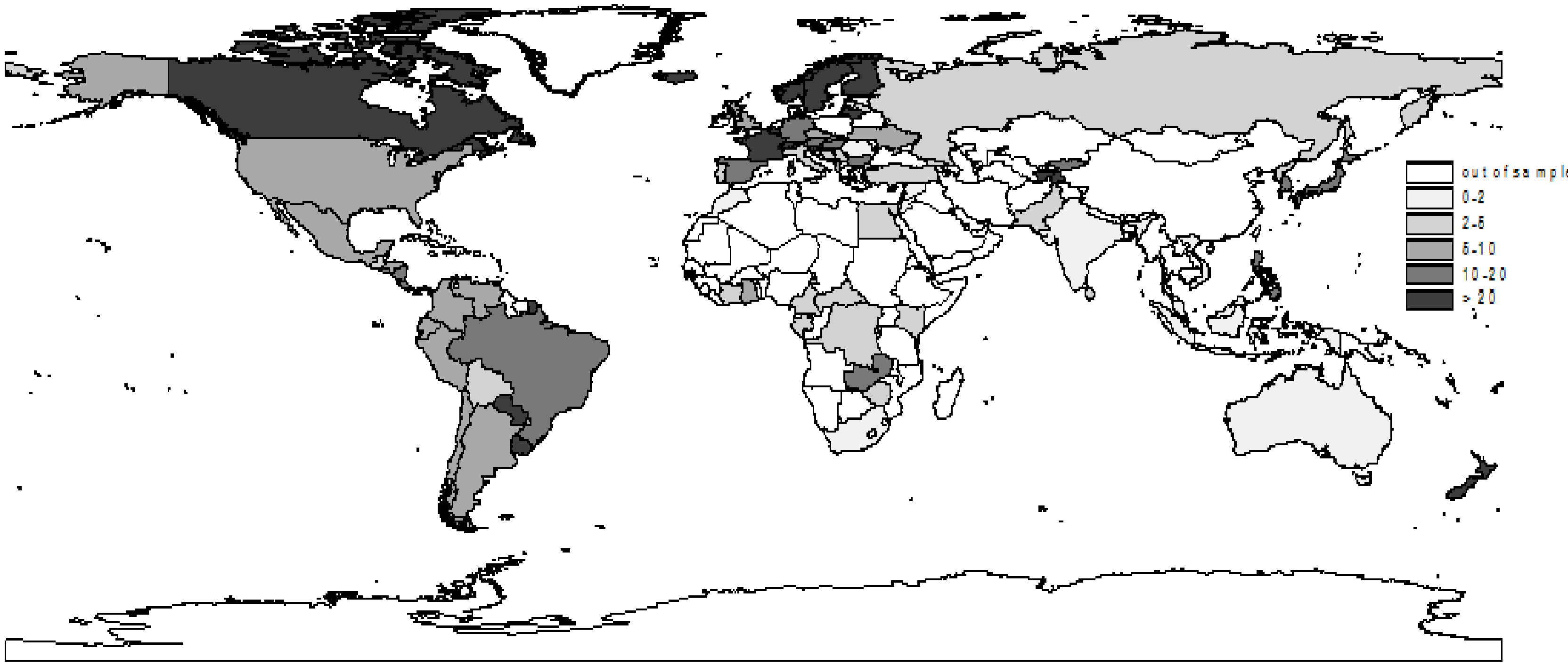
Wei M, Patadia S, Kammen DM (2010). Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US? Energ Policy 38(2):919-931.

Table 1
Non-CO2 generating energy share (%)

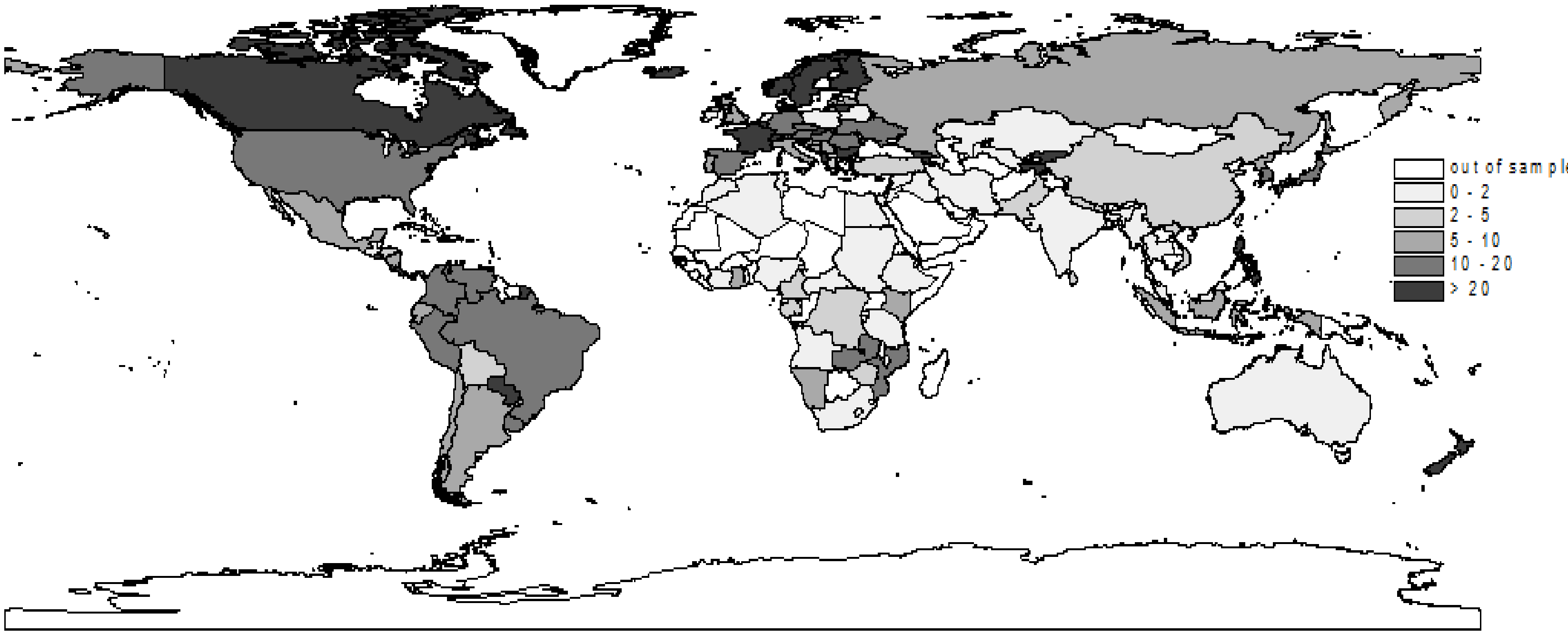
Year	Average	Maximum		Minimum	
		Country	**%**	**Country**	**%**
1990	5.11	Sweden Iceland Paraguay	50.87 67.04 76.03	Belarus Cyprus Estonia	0 0 0
1991	5.19	Sweden Iceland Paraguay	52.26 70.1 79.5	Belarus Cyprus Estonia	0 0 0
1992	5.21	Sweden Iceland Paraguay	49.33 68.31 73.86	Belarus Cyprus Estonia	0 0 0
1993	5.37	Sweden Iceland Paraguay	48.23 68.36 82.31	Cyprus Estonia Belarus	0 0 0.01
1994	5.60	Tajikistan Iceland Paraguay	57.91 67.77 87.3	Cyprus Estonia Belarus	0 0 0.01
1995	5.64	Tajikistan Iceland Paraguay	56.41 69.44 92.21	Estonia Belarus Cuba	0 0.01 0.05
1996	5.67	Tajikistan Iceland Paraguay	59.35 67.67 95.89	Estonia Belarus Algeria	0 0.01 0.05
1997	5.68	Tajikistan Iceland Paraguay	55.08 69.26 100.05	Estonia Belarus Algeria	0 0.01 0.03
1998	5.81	Tajikistan Iceland Paraguay	54.06 70.31 101.41	Belarus Estonia Algeria	0.01 0.01 0.07
1999	5.88	Tajikistan Iceland Paraguay	59.27 73.98 108.55	Belarus Estonia Algeria	0.01 0.01 0.07
2000	6.08	Tajikistan Iceland Paraguay	56.13 74.33 119.48	Belarus Estonia Algeria	0.01 0.01 0.02
2001	6.23	Tajikistan Iceland Paraguay	57.57 75.65 99.45	Belarus Estonia Algeria	0.01 0.01 0.02
2002	6.18	Tajikistan Iceland Paraguay	61.26 74.9 106.72	Belarus Estonia Algeria	0.01 0.01 0.02
2003	6.14	Tajikistan Iceland Paraguay	64.75 75.02 112.3	Belarus Estonia Algeria	0.01 0.03 0.07
2004	6.23	Tajikistan Iceland Paraguay	59.8 74.72 111.52	Belarus Estonia Cuba	0.01 0.05 0.06
2005	6.30	Tajikistan Iceland Paraguay	62.1 75.66 107.08	Belarus Cuba Estonia	0.01 0.05 0.13

2006	6.37	Tajikistan	59.06	Belarus	0.01
		Iceland	78.3	Algeria	0.05
		Paraguay	110.12	Cuba	0.07
2007	6.28	Tajikistan	56.57	Belarus	0.01
		Iceland	80.62	Algeria	0.05
		Paraguay	106.71	Moldova	0.09
2008	6.34	Tajikistan	54.48	Belarus	0.01
		Iceland	82.87	Tunisia	0.06
		Paraguay	106.38	Algeria	0.07
2009	6.54	Tajikistan	58.61	Belarus	0.01
		Iceland	84.23	Algeria	0.07
		Paraguay	99.45	Cuba	0.12

Fig. 1. Non-CO2 generating energy sources: % of total energy use



a) 1990



b) 2009

Fig. 2. σ-convergence

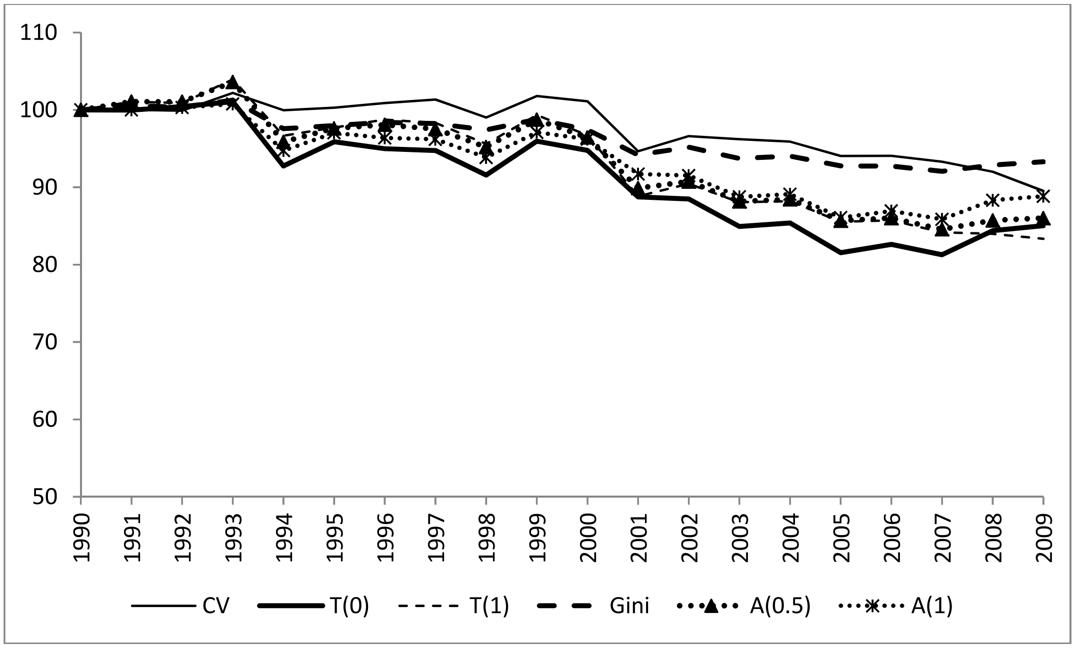
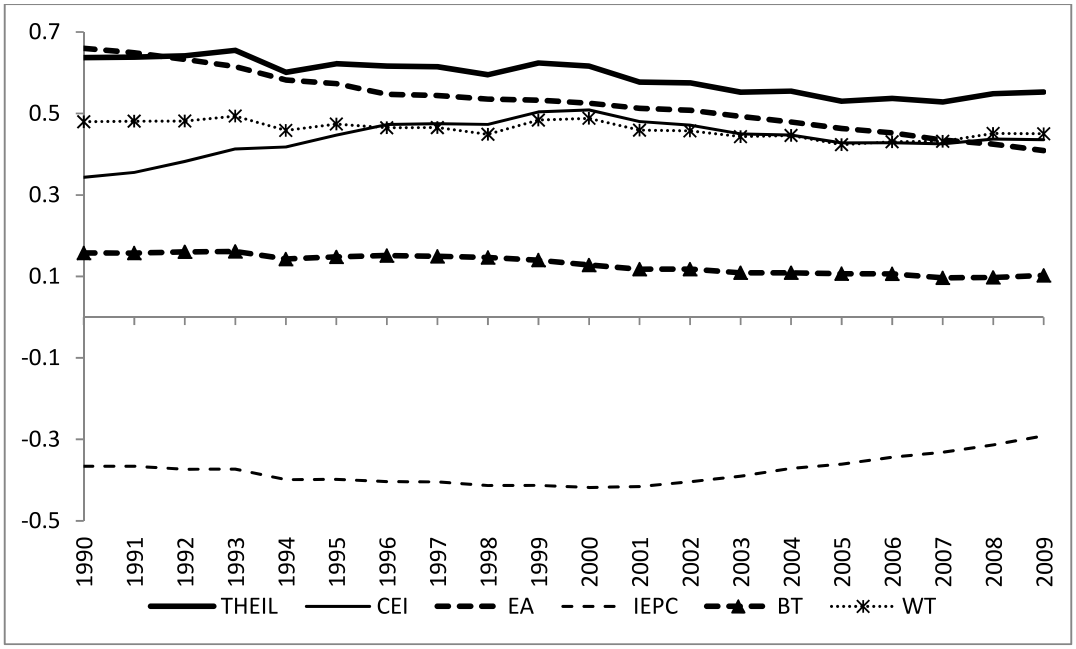


Fig. 3. Inequality decomposition (Theil Index) into explanatory factors



Note: CEI = Clean Energy Intensity; EA = Economic Affluence; IEPC = Inverse of the Energy Per Capita; BT = Between-groups; WT = Within-groups

Fig. 4. Density functions

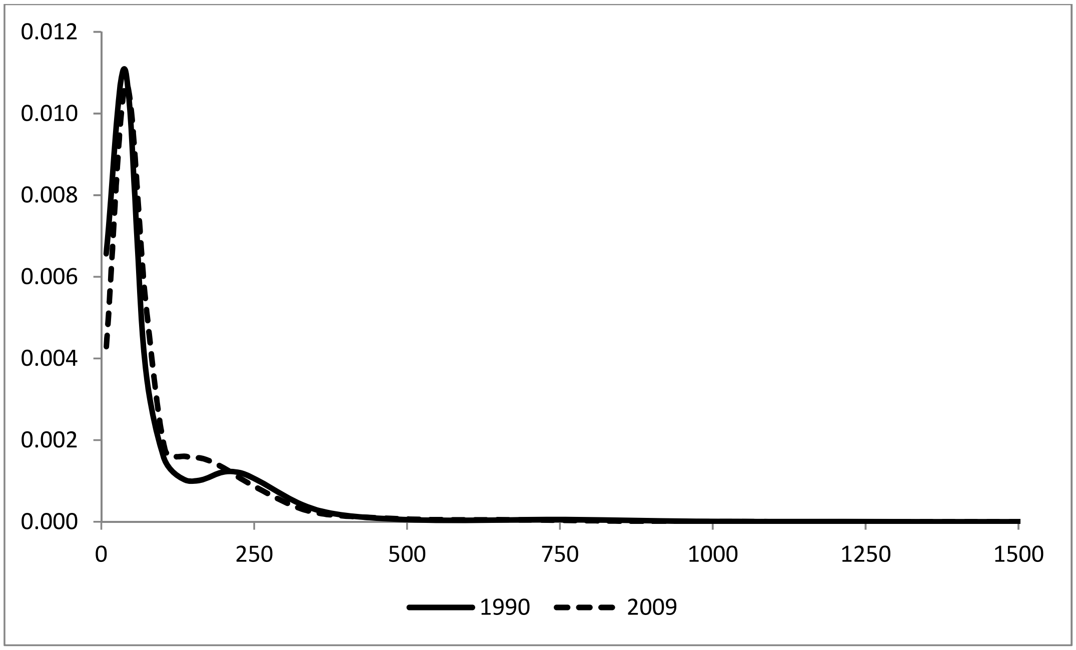


Table 2
Estimated five-year transition matrix, equilibrium distribution and asymptotic half-life

Observations	*Upper bound*	*States*	*Transition probabilities* $p_{ij}(t, t+5)$				
			1	*2*	*3*	*4*	*5*
342	19,40	*1*	**0.827**	0.158	0.000	0.015	0.000
342	50,33	*2*	0.167	**0.699**	0.120	0.012	0.003
342	122,92	*3*	0.003	0.105	**0.792**	0.094	0.006
342	291,45	*4*	0.000	0.000	0.146	**0.784**	0.070
342	$+\infty$	*5*	0.000	0.000	0.003	0.082	**0.915**
Initial distribution v_t			0.200	0.200	0.200	0.200	0.200
Equilibrium distribution			0.179	0.181	0.249	0.201	0.190
Asymptotic half life			11.257				

Note: Observations in the first column are the number of country/year pairs beginning in the respective state at *t*. The four first upper bounds correspond to the 4 quintiles, so that the total of 1,710 observations is divided into five states with equal number of observations. Due to rounding, rows of the transition matrix and both the initial and equilibrium distributions do not always add up exactly to unity.

Table 3
Characterization of mobility degree

Mobility degree	Condition	Bounds
High	More than 50% of countries move to a contiguous state	$d(P) \geq 0.112$
Medium	Between 25% and 50% of countries move to a contiguous state	$0.056 \leq d(P) < 0.112$
Low	Less than 25% of countries move to a contiguous state	$d(P) < 0.056$

Table 4
Normalized distance matrix

States	*Normalized distances* d_{ij}				
	1	*2*	*3*	*4*	*5*
1	0.000	0.041	0.128	0.319	1.000
2	0.042	0.000	0.092	0.290	1.000
3	0.147	0.101	0.000	0.218	1.000
4	0.468	0.408	0.279	0.000	1.000
5	1.000	0.959	0.872	0.681	0.000

Table 5
Population shares, state-by-state and aggregate mobility indexes

p_i	0.118	0.481	0.149	0.190	0.062
$d(P_i)$	0.011	0.024	0.037	0.111	0.058
$d(P)$	0.043				

Table 6

Extended polarization measure $EGR(\alpha, \beta = 1)$

Years	EGR (α=1)			EGR (α=1.3)			EGR (α=1.6)		
	k=2	k=3	k=4	k=2	k=3	k=4	k=2	k=3	k=4
1990	0.3306	0.2597	0.2339	0.2589	0.1690	0.1502	0.2027	0.1047	0.0946
1991	0.3389	0.2597	0.2358	0.2660	0.1681	0.1514	0.2088	0.1033	0.0954
1992	0.3348	0.2561	0.2304	0.2621	0.1655	0.1463	0.2051	0.1013	0.0905
1993	0.3525	0.3326	0.2214	0.2770	0.2554	0.1373	0.2177	0.1995	0.0810
1994	0.3252	0.3075	0.2230	0.2536	0.2350	0.1436	0.1972	0.1825	0.0904
1995	0.3325	0.2891	0.2193	0.2603	0.2066	0.1384	0.2036	0.1472	0.0849
1996	0.3388	0.3006	0.2188	0.2660	0.2231	0.1381	0.2089	0.1671	0.0841
1997	0.3344	0.3087	0.2417	0.2622	0.2359	0.1638	0.2055	0.1833	0.1112
1998	0.3268	0.2941	0.2372	0.2561	0.2174	0.1596	0.2006	0.1622	0.1074
1999	0.3389	0.3103	0.2381	0.2682	0.2362	0.1608	0.2131	0.1826	0.1082
2000	0.3187	0.3134	0.2424	0.2499	0.2406	0.1628	0.1962	0.1879	0.1093
2001	0.3034	0.2925	0.2303	0.2334	0.2224	0.1549	0.1780	0.1718	0.1041
2002	0.3054	0.2940	0.2072	0.2353	0.2237	0.1283	0.1799	0.1729	0.0763
2003	0.2956	0.2787	0.2206	0.2269	0.2068	0.1453	0.1727	0.1549	0.0948
2004	0.2929	0.2816	0.2229	0.2233	0.2096	0.1463	0.1681	0.1576	0.0952
2005	0.2875	0.2771	0.2193	0.2200	0.2067	0.1443	0.1667	0.1559	0.0943
2006	0.2879	0.2719	0.2213	0.2207	0.2012	0.1461	0.1676	0.1502	0.0960
2007	0.2833	0.2144	0.2207	0.2174	0.1351	0.1474	0.1653	0.0790	0.0984
2008	0.2817	0.2241	0.2049	0.2157	0.1434	0.1295	0.1636	0.0862	0.0789
2009	0.2857	0.2273	0.2081	0.2202	0.1455	0.1309	0.1688	0.0874	0.0798
Variation (%)	-13.6	-12.5	-11.0	-14.9	-13.9	-12.8	-16.7	-16.5	-15.7

Table 7

Extended polarization measure $EGR(\alpha, \beta = 1)$ *by components: Simple polarization* $ER(\alpha)$ *and lack of identification* ε

Years	ER (α=1)			ER (α=1.3)			ER (α=1.6)			ε		
	k=2	k=3	k=4	k=2	k=3	k=4	k=2	k=3	k=4	k=2	k=3	k=4
1990	0.4496	0.3219	0.2661	0.3778	0.2312	0.1823	0.3216	0.1669	0.1268	0.1190	0.0622	0.0322
1991	0.4557	0.3232	0.2678	0.3827	0.2316	0.1834	0.3256	0.1668	0.1274	0.1168	0.0635	0.0320
1992	0.4551	0.3212	0.2661	0.3823	0.2306	0.1820	0.3253	0.1664	0.1262	0.1202	0.0651	0.0357
1993	0.4650	0.3885	0.2705	0.3895	0.3114	0.1863	0.3301	0.2555	0.1301	0.1125	0.0560	0.0490
1994	0.4397	0.3678	0.2591	0.3680	0.2954	0.1797	0.3116	0.2428	0.1265	0.1144	0.0604	0.0361
1995	0.4449	0.3496	0.2553	0.3727	0.2672	0.1745	0.3160	0.2078	0.1210	0.1124	0.0605	0.0360
1996	0.4495	0.3590	0.2603	0.3768	0.2814	0.1796	0.3197	0.2255	0.1256	0.1107	0.0583	0.0415
1997	0.4458	0.3719	0.2846	0.3736	0.2991	0.2066	0.3169	0.2464	0.1540	0.1114	0.0632	0.0428
1998	0.4391	0.3520	0.2797	0.3684	0.2753	0.2021	0.3130	0.2201	0.1499	0.1124	0.0579	0.0425
1999	0.4490	0.3697	0.2900	0.3784	0.2955	0.2127	0.3233	0.2420	0.1601	0.1102	0.0594	0.0519
2000	0.4354	0.3693	0.2760	0.3666	0.2965	0.1964	0.3129	0.2439	0.1429	0.1167	0.0559	0.0336
2001	0.4173	0.3522	0.2693	0.3473	0.2821	0.1938	0.2919	0.2314	0.1431	0.1139	0.0597	0.0390
2002	0.4209	0.3557	0.2436	0.3508	0.2854	0.1648	0.2954	0.2345	0.1128	0.1155	0.0617	0.0365
2003	0.4124	0.3408	0.2616	0.3437	0.2689	0.1863	0.2895	0.2170	0.1358	0.1168	0.0621	0.0410
2004	0.4110	0.3411	0.2575	0.3414	0.2690	0.1809	0.2862	0.2170	0.1297	0.1181	0.0594	0.0346
2005	0.4044	0.3359	0.2533	0.3370	0.2656	0.1783	0.2836	0.2148	0.1283	0.1169	0.0588	0.0340
2006	0.4043	0.3337	0.2546	0.3371	0.2631	0.1794	0.2840	0.2121	0.1292	0.1164	0.0619	0.0333
2007	0.4001	0.2831	0.2535	0.3341	0.2038	0.1803	0.2821	0.1477	0.1313	0.1167	0.0687	0.0329
2008	0.4002	0.2886	0.2431	0.3342	0.2079	0.1676	0.2822	0.1507	0.1171	0.1186	0.0645	0.0381
2009	0.4040	0.2918	0.2424	0.3385	0.2099	0.1653	0.2871	0.1519	0.1142	0.1183	0.0645	0.0344
Variation (%)	-10.1	-9.4	-8.9	-10.4	-9.2	-9.4	-10.7	-9.0	-10.0	-0.6	3.7	6.8

Table 8

Population shares p_i *and clean energy shares relative to the average* y_i/μ

Years	2 groups				3 groups						4 groups							
	p_1	p_2	y_1/μ	y_2/μ	p_1	p_2	p_3	y_1/μ	y_2/μ	y_3/μ	p_1	p_2	p_3	p_4	y_1/μ	y_2/μ	y_3/μ	y_4/μ
1990	0.709	0.291	0.366	2.544	0.399	0.375	0.225	0.216	0.663	2.951	0.386	0.319	0.179	0.117	0.210	0.546	1.652	3.851
1991	0.707	0.293	0.356	2.556	0.385	0.383	0.232	0.208	0.628	2.928	0.382	0.325	0.173	0.121	0.207	0.530	1.669	3.817
1992	0.708	0.292	0.357	2.558	0.393	0.384	0.224	0.214	0.659	2.967	0.382	0.315	0.192	0.111	0.208	0.515	1.694	3.898
1993	0.698	0.302	0.334	2.542	0.637	0.227	0.136	0.292	1.390	3.662	0.381	0.319	0.219	0.081	0.217	0.477	1.832	4.494
1994	0.696	0.304	0.368	2.446	0.640	0.233	0.127	0.333	1.380	3.655	0.390	0.334	0.196	0.080	0.255	0.555	1.838	4.435
1995	0.699	0.301	0.363	2.477	0.562	0.230	0.208	0.297	0.907	3.005	0.387	0.308	0.196	0.110	0.257	0.489	1.661	3.879
1996	0.701	0.299	0.358	2.502	0.601	0.256	0.143	0.307	1.213	3.525	0.387	0.314	0.219	0.079	0.256	0.487	1.800	4.464
1997	0.700	0.300	0.363	2.486	0.645	0.222	0.133	0.333	1.342	3.655	0.165	0.509	0.207	0.119	0.137	0.413	1.519	3.816
1998	0.704	0.296	0.376	2.481	0.600	0.249	0.151	0.323	1.138	3.466	0.166	0.504	0.204	0.126	0.136	0.426	1.440	3.728
1999	0.717	0.283	0.374	2.587	0.636	0.224	0.140	0.327	1.283	3.599	0.162	0.517	0.225	0.095	0.122	0.417	1.628	4.169
2000	0.715	0.285	0.391	2.525	0.643	0.218	0.139	0.335	1.316	3.581	0.162	0.480	0.218	0.139	0.122	0.407	1.316	3.581
2001	0.676	0.324	0.383	2.290	0.638	0.220	0.141	0.361	1.305	3.410	0.165	0.497	0.214	0.124	0.126	0.456	1.443	3.579
2002	0.682	0.318	0.382	2.322	0.641	0.218	0.141	0.358	1.321	3.428	0.359	0.323	0.195	0.124	0.259	0.520	1.515	3.594
2003	0.682	0.318	0.395	2.296	0.612	0.246	0.142	0.354	1.240	3.374	0.175	0.482	0.215	0.128	0.150	0.459	1.419	3.499
2004	0.669	0.331	0.386	2.243	0.612	0.244	0.144	0.354	1.226	3.362	0.180	0.462	0.222	0.137	0.152	0.451	1.333	3.434
2005	0.681	0.319	0.406	2.266	0.616	0.243	0.141	0.368	1.228	3.367	0.190	0.467	0.214	0.129	0.165	0.480	1.379	3.487
2006	0.683	0.317	0.408	2.275	0.612	0.243	0.144	0.369	1.187	3.357	0.185	0.470	0.207	0.138	0.156	0.481	1.319	3.414
2007	0.688	0.312	0.419	2.284	0.385	0.407	0.208	0.299	0.726	2.830	0.191	0.481	0.211	0.117	0.163	0.502	1.453	3.587
2008	0.689	0.311	0.419	2.285	0.386	0.402	0.212	0.272	0.756	2.792	0.384	0.306	0.226	0.084	0.271	0.606	1.644	4.015
2009	0.700	0.300	0.423	2.345	0.390	0.390	0.220	0.263	0.755	2.738	0.371	0.322	0.185	0.122	0.254	0.605	1.545	3.490