Centre for Energy Policy and Economics
Swiss Federal Institutes of Technology

Convergence in per capita CO2 emissions

A robust distributional approach

Carlos Ordás Criado, Jean-Marie Grether

CEPE Working Paper No. 70
February 2010

CEPE
Zurichbergstrasse 18 (ZUE E)
CH-8032 Zurich
www.cepe.ethz.ch

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Convergence in per capita CO_2 emissions: a robust distributional approach

C. Ordás Criado* J.-M. Grether†

Abstract

This paper investigates the convergence hypothesis for per capita CO_2 emissions with a panel of 166 world areas covering the period 1960-2002. The analysis is based on the evolution of the spatial distributions over time. Robust measures of dispersion, asymmetry, peakedness and two nonparametric distributional tests - shape equality and multimodality - are used to assess spatial time differences. A robust normal reference bandwidth is also applied to estimate Markov's transition laws and its subsequent ergodic (long-run) distributions. Our results point toward non-stationary, flattening and right-skewed spatial distributions before the oil price shocks of the 1970s and more stable shapes between 1980 and 2000 at the world level and for many country groupings (similar income, geographic neighbors, institutional partners). In the latter period, group-specific convergence patterns emerge with the clearest single-peaked and compact density shapes being reached in the wealthy, well-integrated and European countries during the last years of the panel. No significant multimodality is formally detected in the world distribution over the whole period. The Markov analysis suggests more divergence and larger per capita emissions for the world before stabilization occurs. A variety of steady state distributions are identified in the country subsets.

JEL Classification numbers: C14, D30, Q53, Q56

Key Words: carbon dioxide emissions, air pollution, convergence, distribution dynamics, stochastic kernels, robustness.

*Corresponding author: cordas@ethz.ch. Center for Energy Policy and Economics (CEPE), ETH, Zürichbergstr. 18, 8032 Zürich, Switzerland.

†Institute of economic research (irene), University of Neuchâtel, Pierre-à-Mazel 7, 2000 Neuchâtel, Switzerland.

1 Introduction

While the Kyoto Protocol commitments to prevent global warming expire in 2012, a range of new policy measures has been put forward to pursue the international effort to control greenhouse gas emissions. Among the many options, Aldy (2006) reports that 25% of the over forty proposals surveyed in Bodansky, Chou and Jorge-Tresoni (2004) are based on per capita emissions allocation schemes. The Global Common Institute promotes an approach, dubbed 'Contraction & Convergence' (C&C), which consists of setting a long term sustainable emissions budget and sharing this budget among countries so that per capita levels of pollution are equalized in the long run. The fundamental principle of allocating world emissions according to the same individual "right to pollute" is appealing from an equity point of view[1]. However, the egalitarian rule may not correspond to the 'efficient' distribution, *i.e.* the allocation scheme which maximizes the value of resources. It ignores specific structural characteristics of countries, such as colder climate, natural resource endowments, irreversible investments in energy sources and asymmetric costs/benefits of abatement. Nevertheless, its operational simplicity and its ability to set a "unifying principle that facilitates an international greenhouse warming agreement" (Rose et al. (1998)) between governments has attracted institutional support from rich as well as emerging economies[2]. In the background of this policy debate, an important empirical fact calls for a better understanding of the dynamics of per capita carbon dioxide emissions (CO_2 PCE henceforth): while total emissions keep increasing in most countries, per capita emissions at the global level and in numerous individual countries appear to have stabilized[3]. If national series show some evidence of converging trends, per capita targets may represent a more acceptable basis for political compromises than absolute levels.

This paper explores the cross-country dynamics in CO_2 PCE for the world as a whole as well as for specific subsamples by looking at the *past* and *future* evolution of its spatial distributions. We explicitly address two important questions: (i) has the world spatial distribution of per capita CO_2 emissions been stable since the 1960s or does it tend toward a steady state (possibly multimodal) shape in the long run? (ii) do countries similar in terms of income, geographic neighbors or institutional/political partners display specific converging patterns in per capita carbon levels?

The empirical evidence gathered so far regarding pollution convergence between countries is debated. On the one hand, methods which analyze how the cross-sectional distribution of 'relative' or 'normalized' per capita emissions evolve

[1]Rose, Brandt, Edmonds and Marshall (1998) call this allocation scheme 'egalitarian equity' and define it as an equal right for everyone to pollute or to be protected from pollution.

[2]Copeland and Taylor (2005) argue that, under free trade in goods, there are an infinite number of ways to cut back emissions efficiently. This gives parties abundant leeway to set an initial allocation of permits or pollution targets that addresses distributional or equity concerns.

[3]See McKitrick and Strazicich (2005).

over time show either divergence or persistent gaps worldwide but convergence between industrial or large polluters[4]. On the other hand, time series analyses present ambiguous results, with divergence between OECD members in some studies[5] but convergence within groups of *a priori* more heterogeneous countries[6].

This study revisits the distributional analysis of carbon emissions convergence in a novel fashion. Our first contribution is to greatly expand the number of countries analyzed until now in the database that has been used by many authors. By simply accounting for changes in borders over time, we identify a balanced panel of 166 non-overlapping world areas, spanning the years 1960-2002, which represents about 90% of the countries defined by the World Bank and significantly increases the number and variety of considered areas compared to the previous literature. Second, we explore the world dynamics of per capita emissions not only in relative terms, but also in levels. This departure from common practice is important because, as shown by Stegman (2005), measuring carbon PCE in terms of either percentages or deviations from the contemporaneous arithmetic mean may result in different distribution dynamics depending on the measure used. Third, the (world) spatial distributions of per capita CO_2 emissions are typically highly skewed to the right and suggest the presence of outliers. We conduct a distributional analysis with robust methods which avoid arbitrary deletion of extreme data and prevent their unexpected impact on the convergence measures. Finally, Markov transition matrices/kernels are often used to produce distribution forecasts that are of great interest for policymakers. After estimating the transition laws in a robust manner, we offer for the first time forward projections of spatial CO_2 PCE densities in levels for the world as well for a large variety of country groupings.

Our results highlight important differences in the dynamics of the world spatial distributions of CO_2 PCE, depending on whether per capita emissions are measured in levels or in proportional deviations, and on whether the period under inspection starts before or after the oil price shocks of the 1970s. While the relative data suggest a moderate increase in the pollution gaps during the 1960s followed by a period of stronger cross-country divergence which stabilizes in the 1990s, their unscaled counterparts suggest strong divergence before the oil shocks and later stabilization. Regarding the distribution forecasts, we show that, when transition laws covering the 1960-2002 period are employed, the Markov analysis predicts larger emissions and dispersion compared to current levels, whatever the emissions' measure. If a post-oil shock dynamics (1980-2002) is used instead, the long-run (ergodic) spatial density for the relative series is very close to the one in 2000, while further divergence and larger pollution with a later stabilization is predicted with unscaled CO_2 PCE levels. We identify a variety of clusters of converging economies according to regional, economic and political country groupings.

[4]See Stegman (2005), Nguyen Van (2005), Aldy (2006) or Ezcurra (2007).

[5]See Aldy (2006) and Barrasi, Cole and Elliott (2008).

[6]See Westerlund and Basher (2008) or Panopoulou and Pantelidis (2009).

For most of these subsets, we reject formally the pooling with the rest of the world. However, we find no evidence of significant (multi-)polarization for the world when multimodality is formally tested over the 1960-2002 horizon. This suggests that the convergence club phenomenon of per capita CO_2 emissions is not strong and wide enough to generate statistically significant multiple modes in past distributions.

The rest of the paper is as follows. Section 2 proceeds with an extensive survey of the empirical literature on the dynamics of per capita carbon emissions. Section 3 describes the distributional methodology. Section 4 presents the data and historical trends for world samples as well as for several groupings of countries. The empirical results are shown in section 5 and section 6 concludes.

2 Empirical literature

The evolution of the gaps in per capita CO_2 emissions between countries/regions is explored mainly with four measures of convergence, all borrowed from the income growth literature. The first one, called beta-convergence (β-convergence), captures the idea that countries with lower initial levels of pollution per capita should experience higher pollution growth, and therefore eventually 'catch-up' with the most polluting countries. In the presence of absolute β-convergence, regressing the subsequent period pollution average growth rate for each country on its initial pollution level should result in a negative relationship. In practice, the 'catch up' phenomenon is expected to occur between similar countries whose economic activity took off at different points in time. Thus, economies with structural differences will tend to grow toward their own pollution level, and convergence becomes conditional upon country characteristics. In this case, conditional β-convergence is naturally investigated by adding a set of exogenous explanatory factors to the absolute β-convergence regression[7]. The second empirical measure of convergence, dubbed sigma-convergence (σ-convergence), requires that dispersion across a group of countries decreases over time. Barro and Sala-i Martin (2004, Ch.11.1) show that β-convergence is a necessary but not sufficient condition for the cross-section variance to decrease over time. Note that σ-convergence may fail to capture polarization phenomena in case of tendencies toward multimodality. Stochastic convergence is another approach to convergence based on univariate time-series analysis. Inspired by the work of Carlino and Mills (1993), this method employs unit root specifications, with a constant and with or without a linear trend, for testing to what extent initial departures from some hypothesized (relative) long-run equilibrium in per capita pollution tend to vanish over time. In this framework, rejecting the presence of a unit root in pollution series relative to some group-specific contemporaneous mean indicates that a random shock to the series reverts toward a (potentially null) constant or toward the constant and a trend. Unit root specifications can be estimated with a variety of techniques, designed for individual series or

[7]The shortcomings of β-convergence have been widely discussed in Durlauf, Johnson and Temple (2005).

panel data, under the null of stationarity or nonstationarity and accounting or not for (multiple) structural breaks and for cross-sectional dependencies in the panel statistics. Other variants of stochastic convergence, called pair-wise convergence, have also been suggested by Bernard and Durlauf (1995), Evans (1998) and Pesaran (2007) to tackle directly the dynamics of income differences between pairs of countries and to extend the results of the pair-wise approach to all members of a set of economies. Phillips and Sul (2007) have recently introduced a time-varying factor model based on proportional deviations from the cross-sectional mean which allows for a wide range of (nonlinear) time trends and country-specific heterogeneity.

Finally, the distribution dynamics analysis initiated by Quah (1997, 1993) puts the emphasis on the intra-distributional mobility ('churning') characterizing sequences of cross-sectional distributions over time. It consists of conditioning future spatial distributions of per capita emissions of CO_2 on their past counterparts by assuming that current levels map into future ones according to a time-invariant transition law[8]. This is similar in spirit to a first order autoregression, with distributions as argument instead of scalar or vectors. Limiting (long run or ergodic) distributions can be computed based on transition laws and polarization phenomena detected.

Time-series properties of per capita CO_2 emissions. Three major papers[9] focus solely on the time-series properties of the (log) level of the data. Heil and Selden (1999) are among the first to test for unit roots in carbon dioxide PCE series with level as well as logarithmic data. The null of a unit root is checked for an unbalanced world panel of 135 countries over the horizon 1950-1992 with a country-by-country Augmented Dickey-Fuller (ADF) test and the panel approach of Im, Pesaran and Shin (2003) (IPS) for a constant and trend unit root specification. The unit root null is rejected for 20 (22) countries' level (logarithmic) series as well as for the whole panel against 'trend stationarity for some panel members'. The pre- and post-oil shock periods 1950-1973 and 1974-1992 are investigated separately with the IPS approach and indicate trend stationarity in all cases except in levels for the pre-oil shock period. Therefore, level and logarithmic data may yield different results as an exogenous structural break in 1973 is found only in levels. No information on the national trend's coefficients are provided. Lanne and Liski (2004) propose a country-level investigation for 16 OECD series in logarithms, spanning the years 1870-1998, with an endogenous break unit root test applied sequentially to identify multiple breaks. Among the 10 trend-stationary series identified, non-significant or negative trends are found for 4 countries after the final breaks occurring in the 1970s while the remaining series are positively trended (with/without breaks). In the same vein, with shorter time series but a widely extended number of countries, McKitrick and Strazicich (2005) apply an

[8]As noted by Quah (1993, p.429), there is "no reason why the law of motion of the cross-sectional distribution need be first order, or why the relation need be time-invariant".

[9]A table that summarizes the empirical literature presented in this section is available on the corresponding author's website.

endogenous two-break unit root test to a world as well as 121 national CO_2 PCE series over the years 1950-2000. They find no evidence of a unit root against trend stationarity for the individual world series and identify two breaks in 1968 and 1981 in the deterministic trend. After 1981, the linear trend's coefficient is small in magnitude, negative and not significant. Regarding results at the country level, only 26 out of the 121 series possess a unit root. Moreover, 46 out of the 95 trend-stationary series (48%) have significant positive trends after the final break, 18 (19%) are negatively trended and 31 (33%) are trendless. Note that 60% of the countries experience a significant break between 1973 and 1982. Overall, these three papers highlight three main characteristics of the national time-series on CO_2 PCE : (i) most of them are not stochastically trended, (ii) they display significant structural breaks, mainly located around the oil price shocks when postwar data are used, (iii) and the world CO_2 PCE level as well as a large portion of the national series depict null or decreasing deterministic trends after the last structural break identified.

Convergence in per capita CO_2 emissions. We begin with the β and σ-convergence results, we proceed with the stochastic approach and end with the distributional analysis. To our knowledge, Strazicich and List (2003) (SL2003 henceforth) are the first to explore convergence for CO_2 emissions. They study both absolute and conditional β-convergence for a sample of 21 OECD countries over the period 1960-1997. The conditional β-convergence analysis is carried out based on a set of ad-hoc regressors which capture country-specific characteristics: GDP, GDP squared, gasoline price, population density and a temperature indicator. The regression results indicate that absolute β-convergence holds and that the convergence coefficient remains significant and negative for all investigated combinations of control variables. Among the conditioning factors, only the gasoline price and temperature appear to be significant and possess a negative impact on emissions growth. Brock and Taylor (2004) test absolute as well as conditional β-convergence based on their Green Solow model, by progressively augmenting the simple cross-sectional regression with time-averaged country-specific (estimations of) technological progress in abatement, saving rate, abatement level and effective depreciation rate of capital. The model is tested for OECD countries over the period 1960-1998 and the fits indicate that most of the explanatory power comes from the initial level of pollution, which displays a significant negative effect. Nguyen Van (2005) analyses absolute β-convergence for 100 countries over the period 1966-1996 and finds a significant negative relationship. Finally, Aldy (2006) provides estimations of σ-convergence for 23 OECD series as well as for a 88-country world sample over the period 1960-2000[10]. Based on two distinct measures of dispersion, he shows that the standard deviation of the cross-section CO_2 PCE *in logarithms* decreases steadily for the OECD panel but increases slightly for the world over the period. Then, comparing the interquartile ranges (IQR) for *relative* series in 1960 with those for later decades, he confirms the latter result

[10]See Aldy (2007) for a study on CO_2 convergence between US states.

for OECD countries but without formally rejecting the null of equal dispersion between the reference year 1960 and later decades. Significant divergence is found for the world sample in 1990 and 2000 with the IQR measure. Overall, these studies find β-convergence for the OECD samples as well as at the world level. However, σ-divergence is prevalent for the world while the contrary holds in most of OECD country groups.

Regarding stochastic convergence, SL2003 make use of a linear trend specification in the panel IPS framework to test convergence of the log of relative CO_2 PCE for an OECD panel of 21 countries. The panel statistic validates the existence of convergence among (some) OECD members but no information is provided regarding either the significance level or the sign of the national trends' coefficients. Nguyen Van (2005) analyzes stochastic convergence for a world panel with a constant specification (no trend), the dynamic panel approach of Arrellano and Bond (1991) and the log of relative CO_2 PCE taken every 5-year as well as 10-year periods for each country. Stochastic convergence is accepted with only the 5-year data. Aldy (2006) tests a unit root equation with a linear trend at the country level with an improved version of the Dickey-Fuller test. He finds that only 13 and 3 countries reject the null of a unit root in his world (88 countries) and OECD (23 countries) samples respectively at the 10% level, but he provides no formal panel results. More recently, Barrasi et al. (2008) focus on the 21 OECD countries used in SL2003 and complete the analysis by investigating the individual intercepts/trends' characteristics for the period 1950-2002. Making use of more recent unit root techniques (with trend stationarity under the null), they report pollution divergence across the OECD members, even when the ADF and IPS approaches from SL2003 are employed with methods that improve the size and power of the latter test and account for cross-dependencies. Romero-Ávila (2008) studies a similar OECD sample of 23 countries over the years 1960-2002 with both a constant and a constant-and-trend equations, allowing for an unknown number of endogenous breaks in both specifications, correcting or not for cross-correlation in the panel statistics. Under the null of either stationarity or trend stationarity, he shows that stochastic convergence - *i.e.* (trend-)stationarity - is widely rejected for the whole panel when structural breaks *and* cross-sectional dependencies are ignored but overwhelmingly accepted when they are *both* allowed.

Using the notion of pair-wise convergence *à la* Evans (1998) and a panel unit root test with constant and trend which accounts for cross-sectional dependencies, Westerlund and Basher (2008) establish the existence of group-wise convergence between 16 OECD countries for the period 1870-2002 and for 28 developed and developing countries over the horizon 1901-2002. The existence of numerous clubs of convergence is confirmed over the postwar period 1960-2003 by Panopoulou and Pantelidis (2009). These authors apply the factor model and classification algorithm of Phillips and Sul (2007), and they identify the existence of two balanced convergence clubs at the world level in a context of global CO_2 PCE divergence within the 128-country sample, with evidence of transitioning between the two groups. When two early and late subperiods are considered separately, the 1960-1982 period is characterized by (slow) convergence among all countries, and two main convergence clubs of low vs. large polluters are identified between 1975 and 2003 in a context of divergence between the 128 economies. In addition, they highlight (a) strong convergence over the whole period within the EMU, OECD, high-income groups as well as within several world regions (MENA and EAP), (b) slow convergence between the middle-income and LAC countries and (c) divergence within the low-income group, OPEC and the ECA, SSA and SA areas (see section 4.1 for acronyms). Three main conclusions can be drawn from the empirical literature on stochastic convergence in CO_2 PCE: (i) accounting for structural breaks/nonlinearities in the dynamics as well as cross-sectional dependencies favors the convergence hypothesis in carbon panels, in particular for the OECD countries, (ii) a variety of convergence clubs exists (based sometimes on simple grouping criteria), with possible transitioning between them and variable convergence speeds, (iii) the evidence at the world level is mixed but points toward persistent/increasing differences with potential emergence of a multi-polar world in the future.

Finally, four papers study the intra-distributional dynamics of *relative* per capita CO_2 emissions for large panels of world countries by assuming cross-sectional distributions evolving according to a stable time-invariant (Markovian) first order process (or stable transition probabilities). In a discrete framework, Aldy (2006) warns against the sensitivity of the ergodic (long-run) distributions to the reference period and concludes that 'no meaningful convergence' exists at the world level with a 1-year transition step. However, he reports long-run unimodal distributions with more probability mass in the lower emissions categories compared to the distribution of the last year of the panel, whatever the reference period considered to compute the transition law. Furthermore, projections based on 1960-2000 and 1970-2000 dynamics predict lower variance in the world ergodic distribution. Some hints of bimodal polarization (twin-peaked distribution) also arise with the most recent transitions. Nguyen Van (2005) argues that the time-invariant hypothesis of the transition process is quite robust in a continuous setting with 10-year transitions and that worldwide convergence occurs essentially between the most intensive polluters and the rest of the world as well as within industrial countries. Stegman (2005) confirms Nguyen Van's results for the world to some extent[11] with a panel of 97 countries spanning the years 1950-1999. However, she stresses that centering the data instead of dividing them by the cross-sectional contemporaneous mean would result in no evidence of convergence (but rather persistent gaps) over the *entire* initial distribution's support. Finally, Ezcurra (2007) employs a panel of 87 countries over the period 1960-1999 and provides polarization measures based on an exogenous partitioning of the sample. He shows that cross-country polarization decreases steadily when a two-group splitting is considered and that it remains steady during the 60s but decreases afterwards with a three group par-

[11]Stegman (2005, p.17-18) outlines that the few observations available at the upper relative CO_2 PCE levels may bias severely the stochastic kernel estimates.

tition. He also estimates ergodic densities and conditional densities on income, trade openness and climatic conditions (average annual temperature) for selected years (first and last year of the panel). The ergodic distribution appears to be unimodal and does not collapse over time, suggesting permanent differences in the long run. Regarding the conditional distributions for selected years, the density mass is more concentrated around the average when the data are conditioned upon the per capita income and climatic conditions' variables, while trade openness does not affect the original distributions. Overall, the distributional analysis indicates convergence between industrial economies and between the most intensive polluters and the rest of the world but 'persistent relative gaps' for the remaining emitters. Our distributional approach completes these relative patterns with a level analysis for multiple country sets and proposes a direct comparison between the ergodic shapes and the current distribution.

3 Estimation methods

In order to capture consistently the cross-country convergence process for CO_2 PCE with a distributional approach when heavy asymmetries are present in the data, our first step consists of evaluating the changes in spatial distributions at regular time intervals with robust statistics without imposing constraints on the dynamic process. Section 3.1 proposes a series of simple measures of location, spread, asymmetry and peakedness which offer a more systematic and robust picture in terms of these distributional dimensions. It also introduces two tests devised to check formally the existence of multimodality and time-differences in shapes. In section 3.2, we directly model the growth process which drives the distributional changes over time with a standard state-space approach.

3.1 Comparative statics

Graphical representations of (stacked) annual kernel densities are often used to visualize the evolution of cross-country distributions of CO_2 PCE. In many cases, world subsamples are used to avoid the inclusion of atypical data, which could bias kernel estimation. However, data exclusion introduces potential selection bias. It is therefore important to rely on kernel estimates which are robust to outliers. The annual densities are estimated by the usual kernel method

$$\hat{f}_t(x_{.t}) = \frac{1}{n_t h_t} \sum_{i=1}^{n_t} K\left(\frac{x_{it} - x_{.t}}{h_t}\right) \text{ for } t = 1960, \ldots, 2002 \qquad (1)$$

where n_t denotes the sample size in year t, x_{it} the level of CO_2 PCE in country i, h_t is a fixed smoothing parameter (bandwidth) and $K(.)$ a (gaussian) kernel function. The choice of the bandwidth is key to capturing the most relevant features of the data distribution. In this paper, we use the highly robust smoothing parameter proposed by Zhang and Wang (2009) which is given by

$$\hat{h}_{t,NR}(p) = 1.06 n^{\frac{1}{5}} \hat{Q}(p) \tag{2}$$

where $p \in (0.3, 0.5)$ is a quantile and $\hat{Q}(p)$ is a local dispersion measure which involves different ratios of quantile ranges. The specific range of the parameter p has been shown to provide more robust bandwidths than other standard (fixed bandwidth) approaches in the presence of outliers[12].

In order to identify the inter-temporal changes in the carbon spatial distributions consistently, robust location, scale and shape (quantile-based) statistics are computed and compared with their traditional (moment-based) counterparts. While the median and interquartile range (IQR henceforth) are widespread robust location and scale measures, little attention has been paid to skewness and kurtosis indicators resistant to outliers. Brys, Hubert and Struyf (2006) show that their asymmetry measure, called medcouple, as well as the peakedness estimator proposed by Schmid and Trede (2003) performs well and tolerate up to 25% and 12.5% outliers respectively before the estimator breaks down[13]. Both statistics (defined below) are location and scale invariant[14] and exist for any distribution.

Let $X_n = x_1, x_2, ..., x_n$ be a i.i.d. univariate sample, ordered such that $x_1 \leq x_2 \leq \ldots \leq x_n$, with median $x_{(0.5)}$. Then the medcouple is given by:

$$MC = \underset{x_i \leq x_{(0.5)} \leq xj}{\text{med}} H(x_i, x_j) \tag{3}$$

For $x_i \neq x_j$, the kernel function $H()$ is defined as

$$H(x_i, x_j) = \frac{(x_j - x_{(0.5)}) - (x_{(0.5)} - x_i)}{x_j - x_i} \tag{4}$$

The kernel function $H(.)$ is a standardized difference between the x_js and the x_is to the median and lies between $+1$ and -1. It is positive (negative) when x_j (x_i) lies farther away from the median and it equals zero in the case of a perfectly

[12]The normal-reference bandwidth proposed by Silverman (1986, p.47) is known to be robust to about 25% outliers. The family of bandwidth proposed by Zhang and Wang (2009) is up to two times more robust.

[13]The breakdown value corresponds to the amount of observations that need to be replaced in the sample to make the estimator worthless (arbitrary small/large or meaningless value). The extreme sensitivity of the standard measure of skewness and kurtosis to outliers is illustrated in Brys, Hubert and Struyf (2004, p.996) and Schmid and Trede (2003, p.2).

[14]$S(F_X) = S(F_{aX+b})$, where $S = \{P, MC\}$ from equations (3) and (5).

symmetric distribution[15]. The median of all these kernel values gives the medcouple. A positive (negative) value of MC indicates a right-tailed (or left-tailed) distribution while 0 means symmetry.

The robust peakedness of Schmid and Trede (2003) is defined as

$$P = \frac{x_{(1-p)} - x_{(p)}}{x_{(1-q)} - x_{(q)}} \tag{5}$$

where $0 < p < q < 0.5$ and $x_{(p)}$ is the pth quantile of a univariate sample. The choice of p and q is somewhat arbitrary but following the aforementioned authors, we set $p = 0.125$ and $q = 0.25$, which is a good compromise between robustness and variance of the estimator. In that case, the denominator in equation (5) corresponds to the IQR, a dispersion indicator often used to measure σ-convergence. The peakedness indicator (5) is a ratio of two lengths: the length of the distribution basis divided by some length related to its center. Larger (lower) peakedness over time requires a larger (lower) *relative* increase of the basis with respect to the center. In the presence of both increasing peakedness and IQR, we can state that the expanding basis and center lead to a wider distribution support that suggests global sigma-divergence. Decreasing peakedness and IQR would indicate that both the basis and center of the distribution shrink, driving to a tighter distribution support that points toward global sigma-convergence. Opposite variations in the peakedness and IQR do not provide immediate interpretation in terms of sigma-convergence for both emissions' range. The reader is warned that, due to the location and scale invariance property of the peakedness indicator, a flatter distribution over time does not imply lower peakedness. Given that this measure is not familiar, the following benchmarks could be useful for interpreting the results: for 10000 draws of the $N(0, 1)$, $N(0, 10)$, $U(0, 1)$, and the bimodal normal mixture $N(\mu = (-2, 2), \sigma = (1, 1), prob = (0.5))$ densities, P is respectively 1.70, 1.70, 1.47, 1.33.

Clearly, identifying increasing/decreasing asymmetry and/or peakedness for a distribution is not enough to capture a potential convergence club phenomenon. The literature on income convergence employs multimodality tests[16]. Among the many procedures available, Hartigan and Hartigan (1985) propose the so-called Dip statistic, which measures the degree of departure from unimodality of the empirical cumulative distribution function[17]. Therefore we also control for multimodality

[15]Note that the kernel $H()$ in equation (4) does not apply to all couples (x_i, x_j) of X_n, but only to those for which $x_i \leq x_{(0.5)}$ and $x_j \geq x_{(0.5)}$. In the special case where $x_i = x_j = x_{(0.5)}$, the function $H(x_i, x_j)$ takes the values of 1 for $H(x_{(0.5)}, x_j)$ and all $x_j > x_{(0.5)}$, -1 for $H(x_i, x_{(0.5)})$ and all $x_i < x_{(0.5)}$, and 0 for $H(x_i = x_{(0.5)}, x_j = x_{(0.5)})$ so there are as many zeros as values tight with the median. See Brys et al. (2004, p.998) for discussion.

[16]See Bianchi (1997) or Henderson, Parmeter and Russell (2008), among others.

[17]More precisely and paraphrasing its authors, the Dip test employs the maximum difference, over all sample points, between the empirical distribution function and the unimodal distribution function that minimizes that maximum difference.

in the cross-section distributions. Note that we used (interpolated) critical values tabulated by Maechler and Ringach (2009) and that this test is location and scale invariant.

Finally, rather than computing differences between specific scale and shape statistics over time, we perform pair-wise comparisons between successive spatial distributions in t and $t+s$ and formally check global differences in the distributional shapes. The closeness between two distributions, i.e H_0 : $f(x) = g(x)$ *vs.* H_1 : $f(x) \neq g(x)$, can be checked by using the standard Kolmogorov-Smirnov test (KS test). Noting X_n and X_m two iid samples of size n and m, recall that the KS procedure relies on the maximum distance (called D_{nm}) between the two empirical CDFs F_n and G_m. This test statistic follows a Kolmogorov-Smirnov distribution[18], noted $\sqrt{\frac{nm}{(n+m)}} D_{nm} \xrightarrow{d} K$. We also apply a procedure proposed by Li (1996) which accounts for cross-sectional dependencies between X_n and X_m. The latter test relies on the integrated square difference between $f()$ and $g()$, its empirical statistic $J_n \xrightarrow{d} N(0,1)$ and the test is one-sided[19]. Note that these distributional tests can be carried out to compare either two distributions over time (time poolability or homogeneity of the data over time) or the homogeneity of two groups for the same year (spatial poolability). In the empirical results, we check for both homogeneity concepts.

3.2 Transition dynamics

The comparative-static exercise does not provide precise information regarding neither the mobility of countries between different CO_2 PCE levels (intra-distributional mobility) over time nor the pattern of change of the spatial density in the long run. This section briefly describes the methodology proposed by Quah (1993, 1997) to address both issues. Let x and y denote the CO_2 (relative) per capita emissions of a cross section of countries at times t and $t+\tau$, with $\tau > 0$. The joint, marginal and conditional densities of (x, y), x and $y|x$ for a given τ can be written respectively $f_{t,t+\tau}(x, y)$, $q_t(x)$ and $g_\tau(y|x)$. A natural kernel estimator of $g_\tau(y|x)$ is $\hat{g}_\tau(y|x) = \hat{f}_{t,t+\tau}(x, y)/\hat{q}_t(x)$, where

[18]Noting $D_{mn} = \sup |F_n(x) - G_m(x)|$, $d = \sqrt{\frac{nm}{(n+m)}}$, and when nm is large enough, the critical significance cutoffs for $\alpha = 10\%$, 5% and 1% levels can be approximated by $1.22/d$, $1.36/d$ and $1.63/d$ respectively.

[19]This test requires kernel density fits for $f()$ and $g()$. We employed equations (1) and (2) for that purpose.

$$\hat{f}_{t,t+\tau}(x,y) = \frac{1}{nh_x h_y} \sum_{i=1}^{n} K_x\left(\frac{x-x_i}{h_x}\right) K_y\left(\frac{y-y_i}{h_y}\right) \tag{6}$$

$$\hat{q}_t(x) = \frac{1}{nh_x} \sum_{i=1}^{n} K_x\left(\frac{x-x_i}{h_x}\right) \tag{7}$$

Equation (6) represents the so-called product kernel estimator of the joint distributions. The $K()$ and h terms in the above equations play the same role as in the univariate case (1) in the x and y dimensions. Pagan and Ullah (1999, p.59) indicate that the bandwidths in equation (6) can be computed using an optimal formula for each univariate kernel component. We used a Gaussian kernel and the robust normal reference bandwidth described in equation (2) for that purpose. Further assuming that the mapping between the cross-country density of (relative) CO_2 PCE in times t and $t+\tau$ is time-invariant and first order (future emissions levels in $t+\tau$ depend only on their value in t), $\hat{g}_\tau(y|x)$ represents a transition operator also called stochastic kernel, that can be employed to predict future distributions through the relation

$$\hat{\phi}_{t+\tau}(y) = \int_0^{+\infty} \hat{g}_\tau(y|x)\hat{\phi}_t(x)dx \tag{8}$$

The conditional density term $\hat{g}_\tau(y|x)$ in equation (8) represents the continuous counterpart of a Markov transition matrix and it can be similarly iterated to generate an ergodic (or long run) distribution, see Johnson (2000). The empirical literature on the topic emphasizes that the ergodic patterns are more sensitive to the time window over which the transition law is estimated than to the choice of the transition step τ. We employ the above methodologies to generate ergodic distributions based on different transition periods in a business-as-usual scenario and we compare their shape with the current spatial distribution. This approach allows one to better identify whether convergence or divergence should be expected in the future, and whether the past dynamics generates (multi-)polarization or fragmentation of the spatial distribution in the long run.

4 Data

4.1 Data source and country groupings

As in most papers presented in section 2, our data on CO_2 emissions come from the Carbon Dioxide Information Analysis Centre[20] (CDIAC) and reflect anthropogenic emissions from fossil fuel consumption, cement manufacturing and gas flaring, ignoring fuels supplied to ships and aircrafts. These series are available

[20] See Marland, Boden and Andres (2006).

at several aggregation levels, such as individual countries, geographic regions or the world as a whole. National series capture the time pattern of more than 250 non-overlapping geographic areas for periods ranging from ten years to over two centuries. When all these data are aggregated for all available years, we get total carbon emissions for what we call the CDIAC World. Once we account for changes in borders over time, this large database allows us to build up a balanced panel of 166 non-overlapping national series[21] covering the period 1960-2002. The latter sample, called CDIAC166 henceforth, represents 183 out of the 208 countries (88%) reported by the World Bank (2004) in its CDrom World Development Indicator 2004 (WDI henceforth). Note that 38 series included in the CDIAC166 sample depict rather erratic time patterns, with annual CO_2 PCE growth rates more than doubling/halving for at least one of the years of the 1960-2002 period. We refer to the latter subset as 'outliers' as their impact on non-robust statistics can be significant. Removing the 38 outlying series from CDIAC166 results in a world sample of 128 countries, CDIAC128 henceforth[22].

Regarding the different groupings of countries, the criteria used to build up income and geographic groups are borrowed from WDI. The World Bank defines the following four income categories on the basis of per capita Gross National Income levels in 2002: low or LI (<735$), lower-middle or LMI (736-2935), upper-middle or UMI (2936-9075), high income or HI (>9075$). Countries are also classified into seven world geographic regions: East Asia & Pacific (EPA), Europe & Central Asia (ECA), Latin America & Caribbean (LAC), Middle East & North Africa (MENA), North America (NA), South Asia (SA) and Sub-Saharan Africa (SSA) [23]. Note that we merged the small South Asia group (5 countries) with East Asia & Pacific and that the middle-income (LMI and UMI) countries form a single subset (called MI).

We also put together in groups countries that have a systemic significance at the world level in terms of fossil fuels consumption or global economic weight. We choose to focus on OPEC, OECD countries and the early EU members, the EU15, which embodies the EU founders and successive newcomers prior to the post 2003 Eastern Europe extensions. Given the new geopolitical configuration that emerged from the 2008 financial crisis, the CO_2 PCE dynamics of the Group of Twenty - the G20 - is also explored.

[21] See the list of countries in the appendix. For the reconstructed series and country groupings, see the complementary material on the corresponding author's website.

[22] *Ibid.*

[23] Most of the CDIAC166 areas are equivalent to the world countries listed in WDI. However, some CDIAC166 areas encompass several WDI countries that belong to the same geographic area but that may possess different income per capita levels. Therefore some sample adjustments are necessary to match the WDI groupings criteria with the CDIAC166 areas.

4.2 Historical trends

Figure 1 displays graphical patterns of total, per capita and relative per capita CO_2 emissions for the world (CDIAC World, CDIAC166 and CDIAC128) samples as well as for the main country groupings (essentially income and geographical groups plus OECD, EU15 and the G20). Table 1 provides summary statistics for the whole 1960-2002 period. Columns 2 to 4 concern total emissions and report for each country/area initial and terminal total emissions, with the corresponding emissions share for each country/aggregate group relative to the reference sample CDIAC166. The emissions' average growth rate over the years 1960-2002 is provided in column 4. Similar statistics for carbon emissions in per capita terms are presented in columns 5 to 7 and their relative counterparts (relative to the arithmetic yearly mean over the 166 CDIAC areas) are in column 8 to 10.

In lines 1 to 3 in Table 1, we can see that the CDIAC166 sample accounts for almost 96.8% (94.7%) of total emissions of the CDIAC World in 1960 (2002), while the world sample without outliers CDIAC128 represents a fair 96.3% (91.3%) share of total emissions. The three world samples display very similar trends. Between 1960 and 2002, CDIAC World emissions went up from 2577 to 6973 thousand millions of metric tons, which represents an average growth rate of 2.4% per year. In per capita terms, the increase over that period is about 0.6% per year for the three world samples, while the rate of growth is negative for the relative series (-1.4%).

If we focus on selected individual countries from lines 4 to 13, we can see that the USA is by far the largest individual total fossil-fuel carbon emitter in 1960 and 2002, with respectively 32% and 24% of CDIAC166 world's emissions. In 1960, Germany and China were at the second and third position, with respective shares of 8.9% and 8.1%. By 2002, while Germany managed to stabilize total emissions at its 1960 level, emerging economies such as China and India strongly increased their total emissions (by 3.6% and 5.7% per year respectively) and share (+6.4% and +3.7%) in the CDIAC166 world. Note that the Chinese and Indian emissions are far below those of more advanced economies both in relative and per capita terms. Luxembourg, UK, Germany and USA were the only rich and diversified economies producing over 3 metric tons (mt henceforth) CO_2 PCE in 1960. These levels decreased over the period for the three European countries while US emissions have kept increasing on average by 0.5%. By 2002, Luxembourg, USA, Australia and Canada were the only *diversified and advanced* economies producing more than 4 mt CO_2 PCE, *i.e.* four times the world per capita level, and more than 2.5 times the CDIAC166 average. The largest growth in total emissions since 1960 took place in oil-producing countries (such as the United Arab Emirates or Qatar).

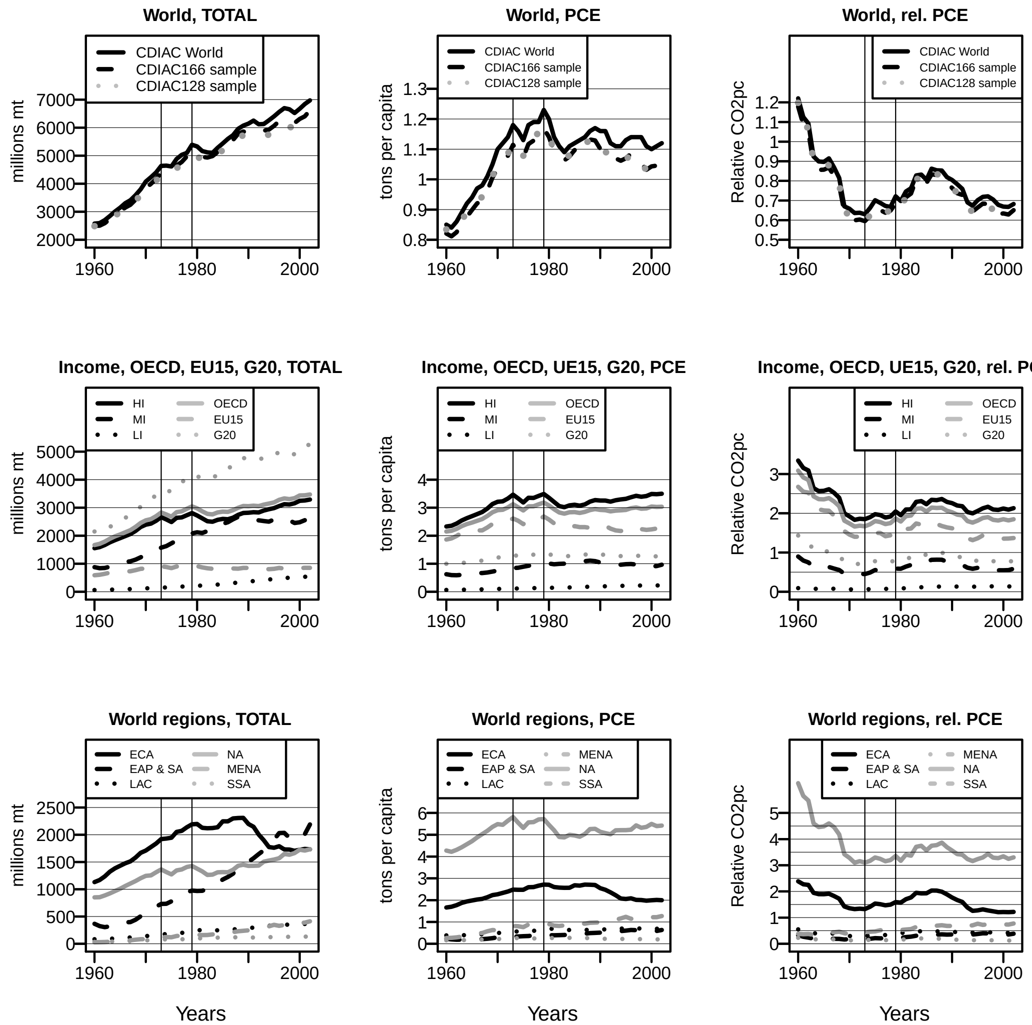
Regarding the time trends in Figure 1, it is very clear on the left graphs that total emissions for all samples (world, income, regions, etc) were rising quickly

Table 1: World carbon dioxide emissions. Summary statistics for the period 1960-2002

Country / group	Levels (in thousand mt)			Per capita (in mt)			Rel. per capita		
	1960 (%)	2002 (%)	annual growth 60-02	1960 (rk.)	2002 (rk.)	annual growth 60-02	1960 (rk.)	2002 (rk.)	annual growth 60-02
World									
CDIAC World	2577.0 (103.2%)	6973.0 (105.3%)	2.4%	0.85 (36)	1.12 (70)	0.7%	1.22 (36)	0.68 (70)	-1.4%
CDIAC166	2497.9 (100.0%)	6621.2 (100.0%)	2.3%	0.82 (39)	1.07 (72)	0.6%	1.18 (39)	0.65 (72)	-1.4%
CDIAC128	2486.0 (99.5%)	6400.2 (96.6%)	2.3%	0.83 (38)	1.07 (72)	0.6%	1.20 (38)	0.65 (72)	-1.4%
Selected countries									
Australia	24.1 (1.0%)	97.1 (1.5%)	3.3%	2.32 (11)	4.97 (11)	1.8%	3.33 (11)	3.02 (11)	-0.2%
Canada	52.6 (2.1%)	140.9 (2.1%)	2.4%	2.88 (8)	4.41 (14)	1.0%	4.14 (8)	2.69 (14)	-1.0%
China	212.9 (8.1%)	957.2 (14.5%)	3.6%	0.33 (64)	0.75 (86)	2.0%	0.47 (64)	0.45 (86)	-0.1%
India	32.9 (1.3%)	332.7 (5%)	5.7%	0.07 (160)	0.32 (109)	3.6%	0.11 (160)	0.2 (109)	1.5%
Germany	222.2 (8.9%)	219.3 (3.3%)	-0.0%	3.07 (5)	2.66 (25)	-0.3%	4.40 (5)	1.62 (25)	-2.3%
Luxembourg	3.1 (0.1%)	2.6 (0.03%)	-0.5%	10.0 (2)	5.71 (9)	-1.3%	14.4 (2)	3.48 (9)	-3.3%
Qatar	0.048 (0.0%)	9.9 (0.1%)	13.5%	1.06 (28)	12.52 (2)	6.0%	1.52 (28)	7.62 (2)	3.9%
U. Arab. Emir.	0.003 (0.0%)	25.6 (0.4%)	24.1%	0.03 (139)	10.49 (3)	15.0%	0.04 (139)	6.39 (3)	12.7%
UK	159.3 (6.4%)	148.1 (2.2%)	-0.2%	3.04 (6)	2.47 (31)	-0.5%	4.37 (6)	1.51 (31)	-2.5%
USA	798.6 (32.0%)	1592.4 (24.0%)	1.7%	4.42 (4)	5.53 (10)	0.5%	6.35 (4)	3.37 (10)	-1.5%
Income									
HI	1554.4 (62.2%)	3290.0 (49.7%)	1.8%	2.33 (11)	3.50 (19)	1.0%	3.34 (11)	2.13 (19)	-1.1%
MI	878.2 (35.2%)	2703.1 (40.8%)	2.7%	0.62 (43)	0.96 (73)	1.0%	0.90 (43)	0.58 (73)	-1.0%
LI	61.9 (2.5%)	564.0 (8.5%)	5.4%	0.06 (118)	0.23 (116)	3.1%	0.09 (118)	0.14 (116)	1.0%
Geogr. areas									
EAP & SA	366.2 (14.7%)	2189.5 (33.1%)	4.3%	0.23 (76)	0.63 (92)	2.4%	0.32 (76)	0.38 (92)	0.4%
ECA	1131.0 (45.3%)	1732.1 (26.2%)	1.0%	1.67 (20)	1.99 (47)	0.4%	2.39 (20)	1.22 (47)	-1.6%
LAC	83.3 (3.3%)	354.2 (5.3%)	3.5%	0.38 (61)	0.66 (92)	1.3%	0.55 (61)	0.40 (92)	-0.7%
MENA	27.9 (1.1%)	412.0 (6.2%)	6.6%	0.27 (70)	1.27 (65)	3.8%	0.38 (70)	0.77 (65)	1.7%
NA	851.2 (34.1%)	1733.6 (26.2%)	1.7%	4.27 (5)	5.42 (11)	0.6%	6.14 (5)	3.30 (11)	-1.5%
SSA	34.9 (1.4%)	135.7 (2.1%)	3.3%	0.16 (88)	0.21 (120)	0.6%	0.23 (88)	0.12 (120)	-1.4%
Other groups									
EU15	588.6 (23.6%)	853.3 (12.9%)	0.9%	1.86 (16)	2.25 (39)	0.4%	2.67 (16)	1.37 (39)	-1.6%
Ex-USSR	395.1 (15.8%)	587.3 (8.9%)	0.9%	1.74 (20)	2.06 (45)	0.4%	2.50 (20)	1.25 (45)	-1.6%
G20	2149.3 (86.0%)	5296.3 (80.0%)	2.2%	1.00 (32)	1.30 (65)	0.6%	1.43 (32)	0.79 (65)	-1.4%
OECD	1667.4 (66.8%)	3470.1 (52.4%)	1.8%	2.15 (12)	3.03 (23)	0.8%	3.08 (12)	1.84 (23)	-1.2%
OPEC	39.6 (1.6%)	430.5 (6.5%)	5.8%	0.20 (78)	0.81 (84)	3.3%	0.29 (78)	0.49 (84)	1.2%

Source: Author's own calculations with CO_2 data from Marland et al. (2006) and population series from U.S. Census Bureau (2006). The sample CDIAC128 corresponds to the sample CDIAC166 once erratic countries are removed. The growth rates are geom. averages over the whole period. 'mt' stands for metric tons, (%) corresponds to emission shares relative to the total CDIAC166 emissions while (rk) is the rank with respect to the national series included in CDIAC166. The income and geographic grouping criteria are based on World Development Indicators (2004). HI, MI and LI stand for high-, middle- and low-income, EAP = East Asia & Pacific, ECA = Europe & Central Asia (ECA), LAC = Latin America & Caribbean, MENA = Middle East & North Africa, NA = North America, SA = South Asia and SSA= Sub-Saharan Africa.

Figure 1: Time trends in world CO_2 emissions. Period 1960-2002.



Notes: Figures on CO_2 emissions and population come from Marland et al. (2006) and U.S. Census Bureau (2006) respectively. CO_2 emissions come exclusively from fossil fuel consumption, cement production and gas flaring. 'mt' stands for metric tons. The income and geographic countries' groupings are based on World Bank (2004). HI, MI and LI stand for high-, middle- and low-income, EAP = East Asia & Pacific, ECA = Europe & Central Asia (ECA), LAC = Latin America & Caribbean, MENA = Middle East & North Africa, NA = North America, SA = South Asia and SSA = Sub-Saharan Africa. The vertical lines plotted correspond to the 1973 and 1979 oil price shocks. Relative CO_2 PCE is calculated with respect to the yearly arithmetic mean over the 166 CDIAC areas.

before the 1970s oil shocks (vertical lines), and kept increasing afterward at a lower pace. The aggregate emissions for the CDIAC World rose by roughly 2750 millions mt (+107%) from 1960 until 1980 and 1640 million mt (+31%) during the 1980-2002 period. The growth rates for the CDIAC166 and CDIAC128 samples are slightly lower. These trends are confirmed at the level of income categories. The European & Central Asia group is the only geographic grouping that reduced its total emissions, by -21%, after the second oil price shock (due to the USSR's collapse). Regarding the political groupings, the G20 happen to be the top polluting group as its members emit roughly 80% of the CDIAC166 total emissions since 1960, with a +92% increase between 1960 and 1980 and +28% during the 1980-2002 period. However, the most striking empirical fact comes from the series in per capita terms: most of the country groupings clearly stabilize their respective level either after the first or the second oil shock. In that respect, our data are in line with McKitrick and Strazicich (2005).

5 Distribution results

The empirical section[24] is divided broadly into two parts. In section 5.1, a world analysis is carried out with series in per capita as well as in relative terms. The comparative statics is conducted every decade from 1960 to 2000 and includes a comparison between the robust location, scale and shape statistics and their traditional moment-based counterparts. The intra-distribution dynamics is performed with 10-year ($\tau = 10$) transition laws estimated over the periods 1960-2002, 1970-2002, 1980-2002 and 1990-2002, and the subsequent ergodic densities are compared with the spatial density for the near-term year 2000.

In the subgroups' results in section 5.2, the relative series' analysis is dropped due to space constraints. The comparative statics is carried out for each country grouping exclusively with robust measures and for the years 1960, 1980 and 2000. Omitting the intermediate decades does not modify the global picture. Spatial density fits for each decade are nevertheless reported and the ergodic densities for each group are shown beside the yearly density plots[25].

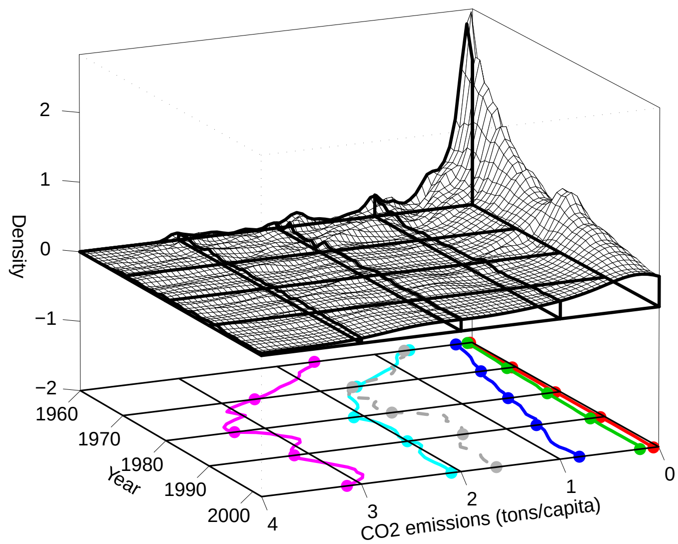
5.1 World convergence

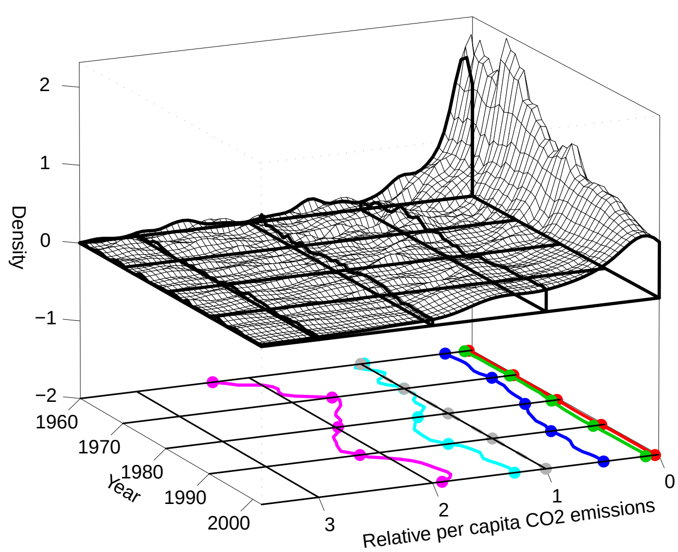
The evolution of the CO_2 PCE cross-sectional densities for the CDIAC166 world panel is presented on the top panel of Figure 2. We can clearly see that the mass of the highly peaked and right-skewed carbon density in 1960 tends to migrate toward larger CO_2 PCE levels over time. This feature is particularly strong during the 1960s but the carbon distributions become more stable after the oil price shocks. The cross-sectional mean (dotted line drawn on the floor of the 3-dimensional plot) is influenced by large values while the median keeps increasing at a more constant pace, which slows down around year 1980. The lower panel of Figure 2 shows how the scaling of the data relative to the cross-sectional mean modifies the graphical pattern. The related densities appear to be roughly stable during the 1960-1970

[24]All the computations in the paper are made using *R.2.9.2* software, see R Development Core Team (2009), and the contributed packages *adapt 1.0-4* of Lumley and Maechler (2007), *diptest 0.25-2* of Maechler and Ringach (2009), *quantreg 4.44* of Koenker (2009), *moments 0.11* of Komsta and Novomestky (2007) and *np 0.30-3* of Hayfield and Racine (2008).

[25]Note that the group analysis exclusively reports the time and spatial poolability tests carried out with the methodology of Li (1996). The Kolmogorov-Smirnov procedure yields identical conclusions in the vast majority of the cases.

Figure 2: Cross-section densities of the world per capita CO_2 emissions. Period 1960-2002.





Notes: the red, green, navy blue, sky blue and magenta lines drawn on the floor represent respectively the 12.5%, 25%, 50%, 75% and 87.5% cross-sectional quantiles over time and are computed with a locally linear nonparametric quantile regressions, see Koenker (2009). The grey dashed line is the cross-sectional arithmetic mean, slightly smoothed with a kernel regression. The univariate cross-sectional kernel densities are estimated with a Gaussian kernel and Zhang and Wang's (2009) robust normal reference bandwidth with $p \in (0.3, 0.5)$.

period, flattening between 1970 and 1990 and staying rather steady afterwards. The reader can check in Figure 7 in the Appendix that these dynamics remain fairly similar when outliers are removed.

Table 2 provides the distributional statistics and tests for cross-section carbon densities of the CDIAC166 world panel for each decade from 1960 to 2000. The median and spread for the relative CO_2 PCE series can be easily obtained from the latter table. Since the asymmetry, peakedness and Dip statistics are scale- and location-invariant, their values hold for the relative series as well. As some of the scale and shape measures based on moments behave erratically, and do not allow any precise inference, we interpret only robust figures. First, the median for the CO_2 PCE series grows over the whole period at a decreasing rate, pointing to a permanent shift of the distribution toward larger CO_2 PCE levels which possibly stabilize in the future. The corresponding medians for relative series are $0.24, 0.21, 0.31, 0.50$ and 0.48, and rather suggest an increasing trend in emissions during the mid-years 1970-1990. Second, IQR for CO_2 PCE levels increases strongly during the 1960-1980 period and remains rather steady afterwards. With the related IQR for relative CO_2 PCE at $0.85, 0.96, 1.15, 1.28, 1.17$, dispersion in that case rises more moderately during the 60s, increases strongly between 1970 and 1990 and stabilizes afterward. In terms of sigma-convergence, (relative) CO_2 PCE series display strong (moderate) divergence worldwide during the 60s, moderate (stronger) divergence in the 70s (1970-1990) and relatively stable spread since 1980 (1990).

Third, the asymmetry measure (MC) indicates that the cross-sectional densities are right-tailed during all decades and that asymmetry decreases after the 70s oil crises. Fourth, peakedness decreases over time with a large drop between 1960 and 1970. Note however on the upper panel of Figure 2 that percentile 87.5 minus percentile 12.5 (the numerator of the peakedness indicator) increases during the years 1960-1970, signaling sigma-divergence in CO_2 PCE levels between the most intensive polluters and the rest of the world, while the relative series on the lower plot exhibit a decreasing difference in these percentiles during that period, suggesting convergence instead[26]. Fifth, no significant departure from unimodality is detected with the Dip test over time, which points towards the absence of multi-polarization at the world level. Finally, both KS and Li's tests show a significant difference between the CO_2 PCE distributions in 1960 and 1970 but none for the next successive pairs of decades and confirm the strong changes in the spatial distribution over the early years. By contrast, the KS and Li's procedures suggest similar spatial distributions throughout the entire time horizon for the relative CO_2 PCE series.

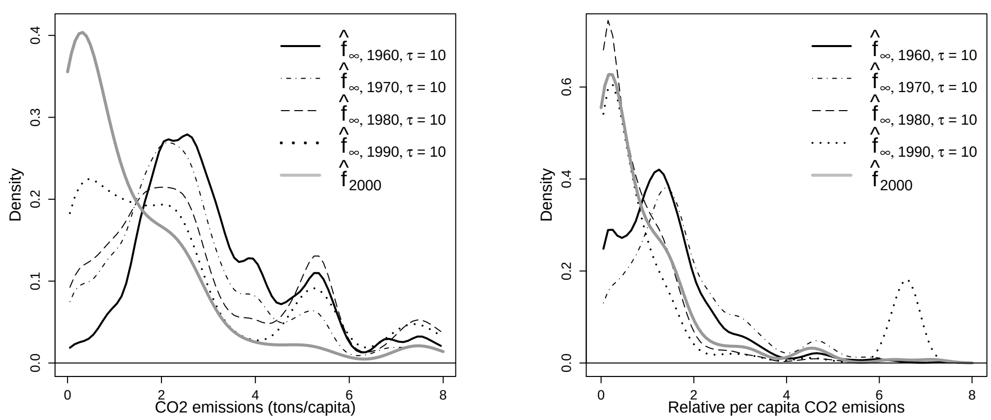
[26]The reader can easily check for the relative series that the difference in percentiles 87.5 and 12.5 went down from 2.19 to 1.67 between 1960 and 1970 (because of the increase of the yearly mean) while the corresponding figures for the unscaled data are 1.53 and 2.78 respectively.

Table 2: World cross-section densities of per capita CO_2 emissions. Location, scale and shape statistics. Period 1960-2000.

Statistic/Test	1960	1970	1980	1990	2000
Location, scale and shape statistics based on moments					
Central tendency (arith. mean)	0.70	1.67	1.72	1.44	1.64
	[0.41,0.91]	[0.92,2.27]	[1.06,2.21]	[1.06,1.74]	[1.11,2.05]
Spread (variance)	2.7	19.3	14.6	5.2	9.8
	[0.6,6.0]	[4.3,42.7]	[3.3,34.1]	[1.9,10.6]	[2.4,22.4]
Asymmetry (skewness)	6.0	6.0	7.0	5.1	6.7
	[4.2,9.8]	[3.9,8.7]	[5.5,11.8]	[4.0,8.8]	[5.4,11.5]
Peakedness (kurtosis)	48.0	47.4	67.4	43.1	63.6
	[14.8,87.8]	[12.0,79.9]	[42.4,126.2]	[28.3,81.4]	[42.6,120.0]
Location, scale and shape statistics based on quantiles					
Central tendency (median)	0.17	0.34	0.54	0.72	0.78
	[0.07,0.21]	[0.14,0.45]	[0.30,0.70]	[0.50,1.06]	[0.49,1.00]
Spread (IQR)	0.59	1.60	1.97	1.84	1.92
	[0.25,0.79]	[1.38,2.15]	[1.51,2.57]	[1.30,2.17]	[1.59,2.46]
Asymmetry (MC)	0.69	0.70	0.63	0.45	0.41
	[0.62,0.90]	[0.59,0.86]	[0.51,0.77]	[0.17,0.62]	[0.25,0.62]
Peakedness	2.60	1.74	1.72	1.62	1.43
	[1.64,3.60]	[1.09,2.08]	[1.20,1.98]	[1.21,1.91]	[0.85,1.59]
Global shape tests					
Unimod. vs multimod. (Dip test)	0.015	0.022	0.014	0.020	0.022
Shape equality (KS test) - levels		0.17**	0.10	0.06	0.06
Shape equality (Li (1996) test) - levels		2.33***	0.40	0.25	0.41
Shape equality (KS test) - relative		0.07	0.10	0.10	0.08
Shape equality (Li (1996) test) - relative		0.37	0.34	0.10	0.42

Notes: In brackets are 95% basic bootstrap confidence limits, see Davison and Hinkley (1997, p.28-29). To avoid negative values for the variance's lower confidence bound, we used the basic percentile method (see *ibid*, p. 202-203). Note that we resampled blocks of full length in the time dimension. IQR and MC stand for interquartile range and medcouple respectively. * and ** indicate 5% and 10% significance levels for the Dip statistic, Kolmogorov-Smirnov (KS) and Li (1996) tests. For the Dip test, spline interpolations from the finite sample tabled critical values have been used. Large samples' asymptotic values are applied in the other tests.

Figure 3: Ergodic densities for the world per capita CO_2 emissions.



Notes: Ergodic shapes based on iterations from stochastic kernels according to the method of Johnson (2000). The conditional densities are estimated with product (gaussian) kernels for the joint. The robust normal reference method of Zhang and Wang (2009) with $p \in (0.3, 0.5)$ is used to get optimal bandwidths.

In summary, the analysis of the world spatial distribution over the postwar period highlights cross-country divergence and larger median emissions for the (relative) CO_2 PCE series during the 1960-80 (1970-90) decades and more stable (relative) emissions and gaps after the 70s oil shocks (1990), leaving the door open for conditional sigma-convergence toward larger and possibly stable emission levels to occur worldwide in the long run. We find significant differences between the successive spatial distributions only between 1960 and 1970 for the series in levels. Finally, we rule out the existence of multi-polarization at the world level over the full timespan.

Figure 3 displays the continuous Markov analysis with the ergodic density plots for the CO_2 PCE series (in relative terms) on the left-hand-side (right-hand-side). The density profiles $\hat{f}_{\infty,1960,\tau=10}$ to $\hat{f}_{\infty,1990,\tau=10}$ correspond to steady state distributions based on 10-year transition laws estimated over the horizons 1960-2002, 1970-2002, 1980-2002 and 1990-2002 respectively. The density $\hat{f}_{2000}$ (in gray) is the near-term spatial distribution in 2000, referred to as the 'current' distribution henceforth. We notice on the left plot in Figure 3 that the ergodic distributions for the level series possess more mass at larger emission levels compared to the current distribution, and globally suggest further divergence and larger emissions with later stabilization. These conclusions are confirmed when integrating the stationary shapes ($\hat{f}_{\infty,1960,\tau=10}$ to $\hat{f}_{\infty,1990,\tau=10}$) over the pertinent ranges and inverting: the respective long-run medians 2.75, 2.25, 2.35, 1.95 and interquartile ranges 2.1, 1.7, 3.1, 2.7 are larger in most cases than the median (0.78) and IQR (1.92) levels in year 2000. A similar result holds with respect to the relative CO_2 PCE steady state densities $\hat{f}_{\infty,1960,\tau=10}$ and $\hat{f}_{\infty,1970,\tau=10}$, where the related long-run medians (1.25 and 1.45) and IQR (1.75 and 1.30) are larger compared to the median (0.48) and dispersion (1.17) in year 2000, while $\hat{f}_{\infty,1980,\tau=10}$ and $\hat{f}_{\infty,1990,\tau=10}$ rather predict sigma-convergence in relative terms, with long-run medians of 0.65 and 1.4 and IQR values of 0.9 and 0.75. We proceed to roughly evaluate the differences in terms of long-run projections for the two CO_2 PCE measures. Noting that the mean emissions per capita over the four estimating periods is about 1.5 mt CO_2 PCE[27], we observe that the 0-2 category for the relative series corresponds to the 0-3 category for the unscaled data. Numerical integration yields proportions of 80.6%, 69.1%, 93.0% and 77.4% countries falling in the 0-3 mt CO_2 PCE range with relative series' dynamics while these magnitudes are smaller in general, 57.0%, 70.5%, 64.0%, 71.2% respectively, with unscaled data. Finally, note that because the $\hat{f}_{\infty,1990,\tau=10}$ projection is based on much less data[28], its shape is less robust and its interpretation will be ignored in the group analysis where smaller samples are employed.

Overall, while the comparative statics suggests a stabilization of the diverging dynamics of the world (relative) CO_2 PCE spatial distributions after 1980 (1990), the transition laws estimated over the whole horizon 1960-2002 predict further cross-country divergence compared to the current level and larger emissions with later stabilization for both emissions' measures. If we rather consider post-oil shock transitions, a similar picture arises for the per capita series while the normalized data predict narrower gaps and larger relative emission levels compared to year 2000. In any case and whatever the starting point and measurement scale, we always find stable and non-degenerated world ergodic densities, which point clearly toward conditional sigma-convergence in the long run (a variety of country-specific steady state emission levels). Compared to other studies, we confirm Ezcurra's (2007) unimodal ergodic shape for the relative series but with essentially post-oil shock transitions. Our results broadly corroborate the sigma-divergence's finding of Aldy (2006) for the relative series over the years 1960-2000 as well as the existence of persistent gaps in the long run. In contrast to his findings, we find lower dispersion in the relative ergodic distributions only when the most recent transition laws are employed. Similarly to Stegman (2005), we highlight that the distribution results are heavily affected by the CO_2 PCE series transformation. Finally, our analysis does not identify the emergence of two (or multiple) modes in the world distribution of relative CO_2 PCE between 1960 and 2002 as some of the results in Aldy (2006) or Panopoulou and Pantelidis (2009) may suggest.

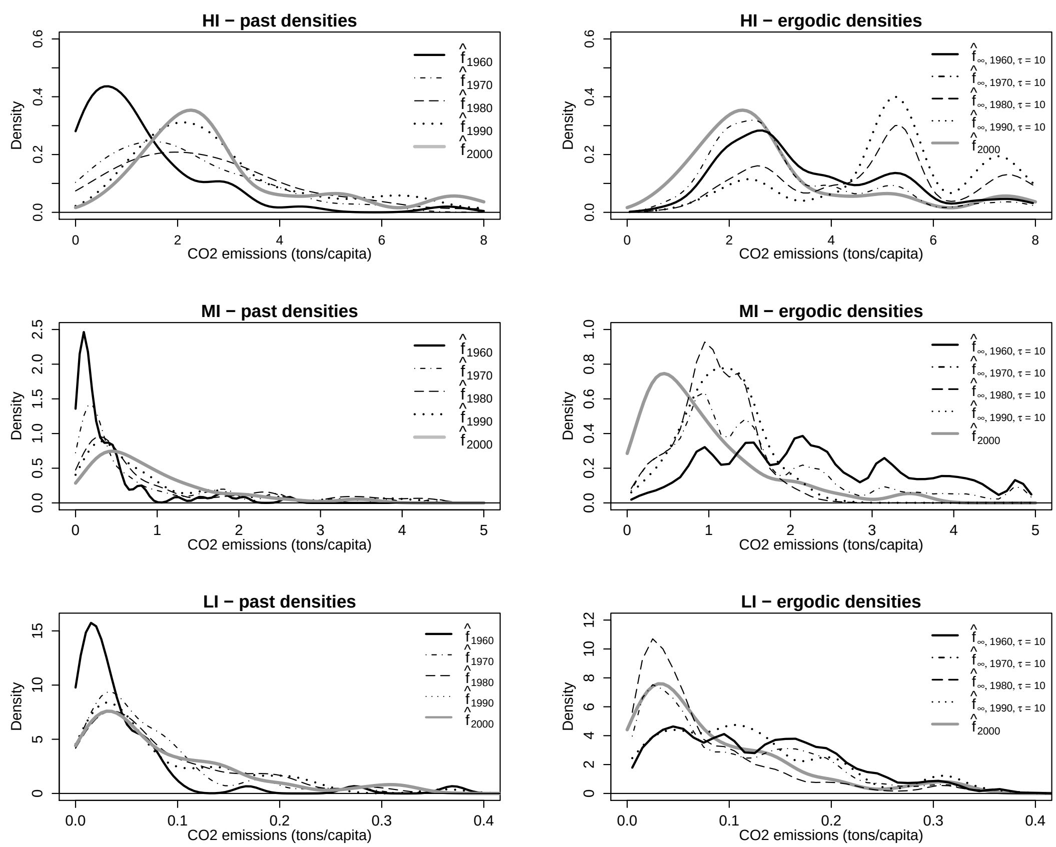
[27] The average per capita emissions over the periods 1960-2002, 1970-2002, 1980-2002 and 1990-2002 are 1.45, 1.58, 1.51 and 1.59 mt CO_2 PCE respectively.

[28] Starting in 1990 allows one to map only three cross-sections (emission levels in 1990, 1991 and 1992) into those observed 10 years later before reaching the end of the time horizon. From another perspective, as noted by Aldy (2006), recent dynamics may be more likely to capture the most relevant economic, technological and institutional factors influencing the transition across pollution levels.

5.2 Convergence within subgroups

Income groups. This subsection empirically investigates how past and future spatial distributions of per capita CO_2 emissions are affected when countries achieve similar levels of per capita income in the terminal year of the panel. The left plots in Figure 4 show the densities estimated for the years 1960, 1970, 1980 ,1990, 2000, denoted $\hat{f}_{year}$. We observe that, similarly to the world sample, the spatial shapes strongly flatten from 1960 to 1980 in all income groups, with a density mass migrating from lower toward larger emission levels. From 1980 to 2000, non-diverging dynamics emerge, particularly in the high-income (HI) and low-income (LI) groups.

Figure 4: Income groups' spatial densities of per capita CO_2 emissions. Period 1960-2000.



Notes: Ergodic shapes based on iterations from stochastic kernels according to the method of Johnson (2000). The conditional densities are estimated with product (gaussian) kernels for the joint. The robust normal reference method of Zhang and Wang (2009) with $p \in (0.3, 0.5)$ is used to get optimal bandwidths.

Looking first at the formal tests in Table 3, we observe that none of the Dip statistics of the multimodality test is significant. We therefore reject the existence of multi-polarization within the income groups. The equality of the spatial distributions is also rejected in all subsets between 1960 and 1980 at the 5% level but accepted between 1980 and 2000. This highlights the importance of the distributional variations in the 60s and 70s whatever the income level. Finally, the spatial poolability of the income groups with the rest of the world is strongly rejected for all years considered.

The descriptive statistics in Table 3 indicate that the median, spread (IQR) and peakedness measures increase quite heavily during the early years 1960 to 1980 in all income groups while the right asymmetry is preserved. These are clear diverging patterns, with distribution basis and center spreading apart toward larger emission levels. After the oil shocks, group-specific behaviors emerge. In the HI economies, the median and spread decrease over time, positive asymmetry increases and peakedness remains steady. This suggests convergence (center and basis shrinking in the same proportion) over that period possibly toward lower emission levels with persistent heavy polluters. In the MI countries, the median rises but IQR, peakedness and positive asymmetry fall. These features also signal absolute/conditional convergence (narrowing basis and center of the distribution) but toward larger emissions. The LI countries display decreasing median and peakedness but slightly increasing IQR and (positive) asymmetry which point toward moderate divergence and decreasing emissions during the post-oil shock horizon.

The ergodic densities drawn on the right-hand-side plots in Figure 4 indicate that the distribution forecasts depend heavily on the time horizon used to estimate the 10-year transition operator. When the full period 1960-2002 is employed, the ergodic shapes (solid black lines) for the three income groups are flatter and emission levels rise globally compared to the levels in 2000 (solid gray lines). By contrast, the post-oil shock transitions 1980-2002 (dashed black lines) favor sharper and single-peaked density profiles around a lower/larger modal emission level compared to year 2000 for the LI/MI economies. The ergodic shape for the HI countries is much more spread and exhibits several modes mainly located at the right of the single peak of year 2000.

In sum, the income groups exhibit sigma-divergence and larger per capita emissions between 1960 and 2000 without hints of multi-polarization. During the subperiod 1960-1980, the diverging and increasing trends are particularly strong in all income subsets. Between 1980 and 2000, we identify sigma-convergence in the HI/MI economies but toward lower/larger emission levels respectively while the LI group exhibits slightly increasing dispersion and lower median emissions. Compared to the spatial distribution in 2000, the distribution forecasts based on 1960-2000 transition laws anticipate further divergence and larger per capita emissions within all income subsets before the steady-state levels are achieved. The post-oil shock transition laws (1980-2002) suggest larger emission levels and multiple modes for the ergodic HI distribution but further convergence toward larger/lower emissions in the MI/LI economies.

Table 3: Income groups' cross-section densities of per capita CO_2 emissions. Location, scale and shape statistics. Period 1960-2000.

Sample (size)	Statistic / Test	1960		1980		2000
High Income (HI) (n=48)	Center (median)	1.77		4.34		3.92
	Spread (IQR)	1.40		2.57		2.02
	Asymmetry (MC)	0.33		0.32		0.52
	Peakedness	1.97		2.83		2.84
	Multimodality (Dip)	0.063		0.044		0.043
	Spatial pool.	30.1^{***}		29.8^{***}		51.1^{***}
	Pair-wise time pool.		5.12^{***}		0.87	
Middle Income (MI) (n=62)	Center (median)	0.17		0.49		0.67
	Spread (IQR)	0.37		1.02		0.84
	Asymmetry (MC)	0.60		0.65		0.40
	Peakedness	1.97		2.18		1.96
	Multimodality (Dip)	0.029		0.028		0.035
	Spatial pool.	28.7^{***}		19.8^{***}		33.9^{***}
	Pair-wise time pool.		4.65^{***}		1.33^{*}	
Low Income (LI) (n=49)	Center (median)	0.024		0.062		0.055
	Spread (IQR)	0.046		0.090		0.110
	Asymmetry (MC)	0.49		0.45		0.52
	Peakedness	1.61		2.03		1.69
	Multimodality (Dip)	0.033		0.033		0.042
	Spatial pool.	167^{***}		120^{***}		133^{***}
	Pair-wise time pool.		1.99^{**}		-0.51	

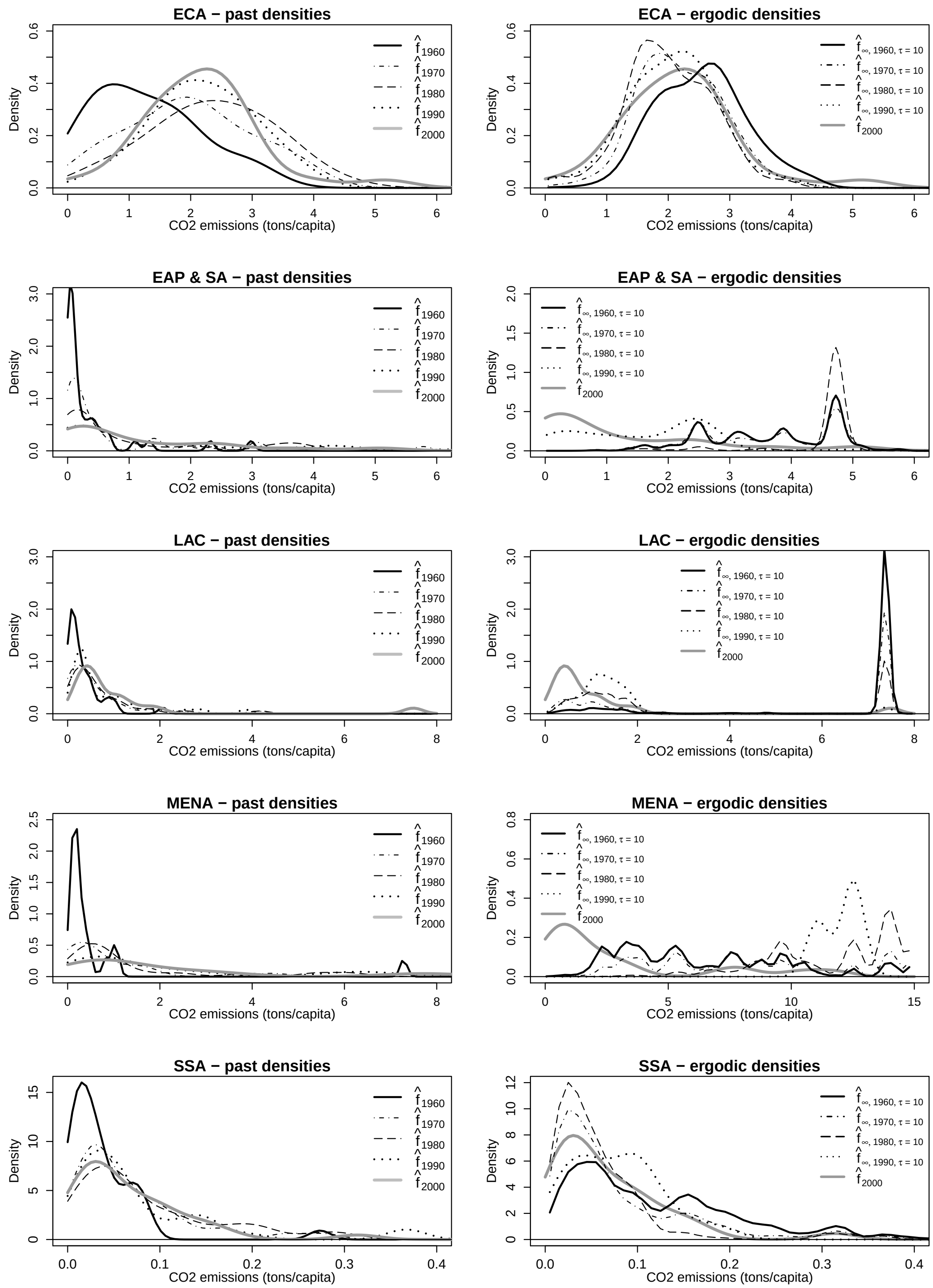
Notes: IQR and MC stand for interquartile range and medcouple respectively. * and ** indicate 5% and 10% rejection levels for the null of unimodality vs multimodality - Dip statistic of Hartigan and Hartigan (1985) - and for the null of distribution equality over time (time poolability) or with the 'rest of the world' (spatial poolability) - J_n statistic of Li (1996).

Geographic groups. Geographic proximity between countries may favor the existence of similar natural resource endowments, weather conditions, technologies or consumption habits which may in return generate a comparable use of fossil fuel. The perspective of regional trading schemes of carbon allowances makes regional emissions dynamics of particular interest. The left density plots in Figure 5 indicate that the early expanding trends and later stabilization in gaps and emissions prevalent worldwide affect most regions. However, East Asia & Pacific and South Asia (EAP & SA) and Middle-East and North Africa (MENA) display particularly spreading apart patterns over the entire timespan.

Starting with the formal tests in Table 4, we identify no significant multimodality within any region and at any time. The spatial pooling of the geographic subsets with the rest of the world is widely rejected except for the EAP & SA countries. Significant differences over time are detected between the distributions of years 1960 and 1980 for most regions (except for EAP & SA) but none between 1980 and 2000.

The statistics in Table 4 show that most regions display larger median emissions

Figure 5: Geographic groups' cross-section densities of per capita CO_2 emissions. Period 1960-2000.



Notes: Ergodic shapes based on iterations from stochastic kernels according to the method of Johnson (2000). The conditional densities are estimated with product (gaussian) kernels for the joint. The robust normal reference method of Zhang and Wang (2009) with $p \in (0.3, 0.5)$ is used to get optimal bandwidths.

Table 4: Geographic groups' cross-section densities of per capita CO_2 emissions. Location, scale and shape statistics. Period 1960-2000.

Sample (size)	Statistic / Test	1960		1980		2000
Europe & Central Asia (ECA) (n=30)	Center (median)	1.13		2.35		2.11
	Spread (IQR)	1.29		1.43		1.17
	Asymmetry (MC)	0.28		0.10		0.02
	Peakedness	1.76		1.52		1.21
	Multimodality (Dip)	0.078		0.045		0.065
	Spatial pool.	27.6^{***}		28.1^{***}		26.4^{***}
	Pair-wise time pool.		3.27^{***}		0.32	
East Asia, Pacific & South Asia (EAP & SA) (n=34)	Center (median)	0.10		0.37		0.65
	Spread (IQR)	0.37		1.75		2.16
	Asymmetry (MC)	0.68		0.70		0.53
	Peakedness	1.73		2.01		1.55
	Multimodality (Dip)	0.044		0.043		0.044
	Spatial pool.	-1.71		-2.26		-1.33
	Pair-wise time pool.		1.21		0.10	
Middle-East & North Africa (MENA) (n=19)	Center (median)	0.19		0.81		1.16
	Spread (IQR)	0.28		2.67		2.52
	Asymmetry (MC)	0.68		0.79		0.71
	Peakedness	2.96		2.12		2.96
	Multimodality (Dip)	0.049		0.055		0.050
	Spatial pool.	27.6^{***}		28.1^{***}		26.4^{***}
	Pair-wise time pool.		2.45^{***}		-0.07	
Latin America & Caribbean (LAC) (n=36)	Center (median)	0.21		0.47		0.60
	Spread (IQR)	0.38		0.84		0.76
	Asymmetry (MC)	0.41		0.52		0.49
	Peakedness	2.04		2.57		2.00
	Multimodality (Dip)	0.036		0.032		0.047
	Spatial pool.	2.0^{**}		6.0^{***}		17.9^{***}
	Pair-wise time pool.		1.43^{*}		0.32	
Sub Saharan Africa (SSA) (n=37)	Center (median)	0.025		0.062		0.055
	Spread (IQR)	0.044		0.088		0.080
	Asymmetry (MC)	0.46		0.51		0.39
	Peakedness	1.62		2.18		1.81
	Multimodality (Dip)	0.038		0.050		0.049
	Spatial pool.	10.1^{***}		68.9^{***}		89.0^{***}
	Pair-wise time pool.		2.16^{**}		-0.11	

Notes: IQR and MC stand for interquartile range and medcouple respectively. * and ** indicate 5% and 10% rejection levels for the null of unimodality vs multimodality - Dip statistic of Hartigan and Hartigan (1985) - and for the null of distribution equality over time (time poolability) or with the 'rest of the world' (spatial poolability) - J_n statistic of Li (1996).

and dispersion between 1960 and 2000. The only exceptions are the ECA countries which converge in the sigma sense. During the early period 1960-1980, median emissions and dispersion more than double in the vast majority of the regions, and more than triple in the EAP & SA and MENA subsets. If we focus on the post-oil shock period 1980-2000, we notice that (a) two regions depict sigma-convergence and decreasing median emissions (ECA and SSA), (b) two other regions exhibit sigma-convergence and increasing median emissions (MENA and LAC) and (iii) one area experiences sigma-divergence and increasing median pollution (EAP & SA).

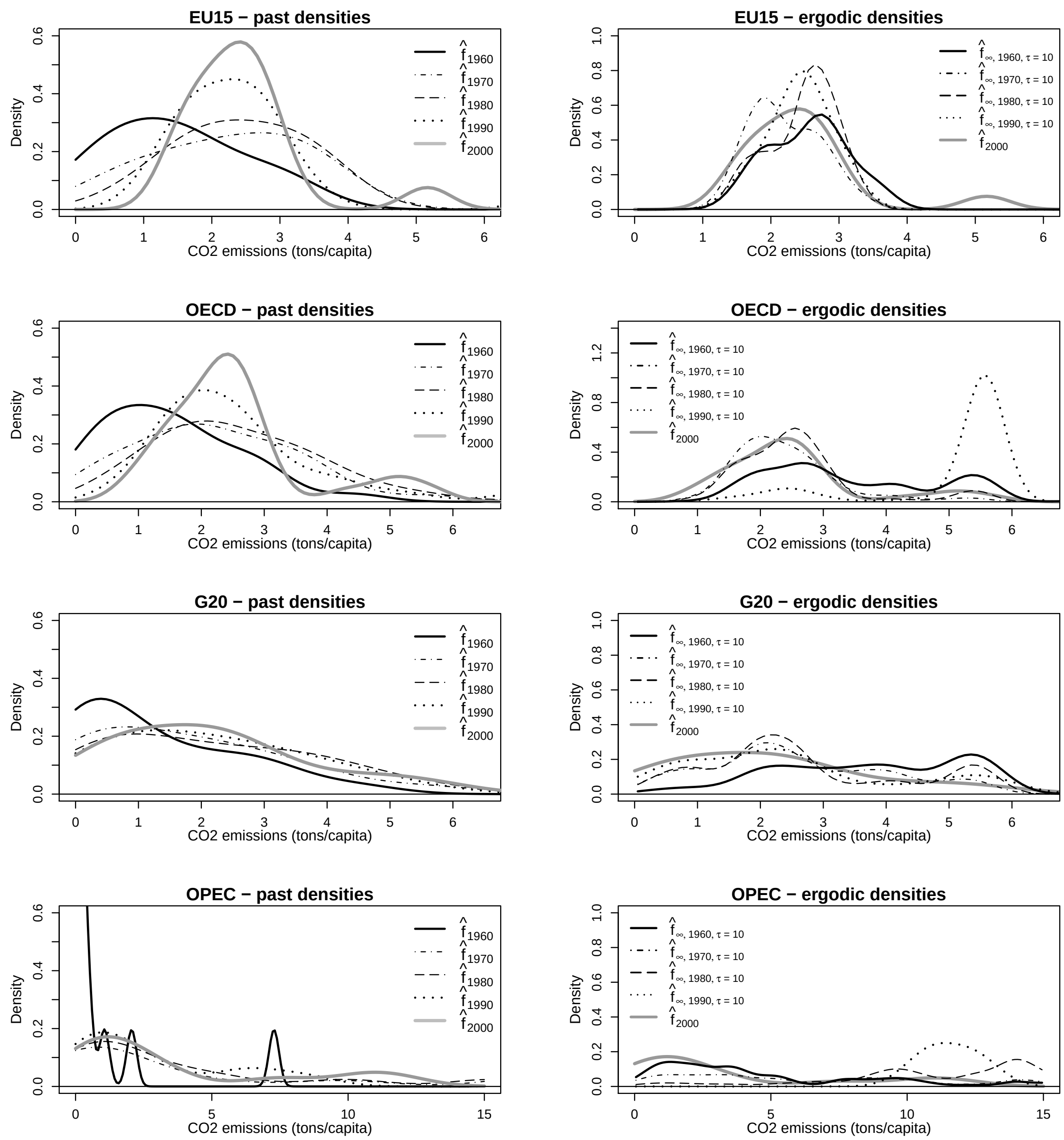
Regarding the Markov analysis, the ergodic densities shown on the right-hand-side plots in Figure 5 indicate that for all regions (except for ECA) the spatial distributions estimated with 10-year transition laws covering the horizon 1960-2002 exhibit much flatter profiles and larger emissions compared to the density in 2000, with possible multimodality in the future. Using post 1970s transitions (1980-2002) instead, the ergodic densities for ECA and SSA are sharper, more compact and possess more mass located at lower emission levels; those for MENA and LAC appear to be relatively fragmented and spread, with several (separated) modes located at larger emission levels; the one for EAP & SA is expected to concentrate mainly within an emission range of roughly 4.5-5 mt CO_2 PCE in the future.

To summarize, every region displays sigma-divergence and larger per capita median emissions over the whole period 1960-2000, except ECA which globally converges. The same picture holds between 1960 and 1980 but with larger variations and divergence in ECA. From 1980 to 2000, sigma-convergence prevails in all regions (but EAP & SA which diverges) with decreasing median emissions in ECA and SSA and increasing median emissions in MENA, LAC and EAP & SA. We formally discard multimodality in the past distributions. The Markov analysis based on 1960-2000 transitions anticipates further divergence and larger emission levels in all regions before the ergodic shapes are reached, except in the ECA area which possesses a distribution in year 2000 close to its steady state. The post-oil shock dynamics (1980-2002) predicts lower emissions and further convergence in two regions: ECA and SSA, and a variety of diverging and polarization patterns toward larger emission levels within the remaining three areas.

Political groupings. This section concentrates on the analysis of countries grouped according to institutional/political characteristics. Starting with the left-hand-side yearly density plots in Figure 6, the similarities between the EU15 and OECD indicate that, as members of OECD, the EU15 countries largely contribute to the peaked density profile that emerges over time in the OECD subset. We also notice the flat shapes of the G20 group which highlight the large pollution gaps existing since the 60s among the G20 economies in per capita terms. Globally, the densities of the four country subsets appear to be unimodal and the expanding trends identified worldwide from 1960 to 1980 seem to be present.

Focusing first on the statistical tests in Table 5, we can see that unimodality is accepted in every subset and for every year considered. The cross-sectional pooling with the rest of the world is rejected in every group and for every year except in OPEC. The equality of the distributions is rejected between 1960 and 1980 at the 10% level in the OECD and OPEC cases but accepted in the EU15

Figure 6: Political groupings' cross-section densities of per capita CO_2 emissions. Period 1960-2000.



Notes: Ergodic shapes based on iterations from stochastic kernels according to the method of Johnson (2000). The conditional densities are estimated with product (gaussian) kernels for the joint. The robust normal reference method of Zhang and Wang (2009) with $p \in (0.3, 0.5)$ is used to get optimal bandwidths.

and G20 subsets while the distributions are formally similar between 1980 and 2000 in all four groups. Consequently, the 1960s dynamics seems to have affected the political country subsets to a lesser extent compared to other grouping criteria.

Turning to the location, scale and shape measures, we notice that, over the full

Table 5: Political groupings' cross-section densities of per capita CO_2 emissions. Location, scale and shape statistics. Period 1960-2000.

Sample (size)	Statistic / Test	1960		1980		2000
	Center (median)	1.62		2.44		2.36
	Spread (IQR)	1.50		1.46		0.71
EU15	Asymmetry (MC)	0.00		0.14		-0.11
(n=15)	Peakedness	1.77		1.51		1.79
	Multimodality (Dip)	0.074		0.058		0.072
	Spatial pool.	9.4^{***}		11.9^{***}		14.7^{***}
	Pair-wise time pool.		0.90		0.42	
	Center (median)	1.33		2.34		2.37
	Spread (IQR)	1.65		1.75		0.79
OECD	Asymmetry (MC)	0.25		0.29		-0.01
(n=29)	Peakedness	1.57		1.59		2.78
	Multimodality (Dip)	0.055		0.043		0.055
	Spatial pool.	13.5^{***}		25.2^{***}		29.2^{***}
	Pair-wise time pool.		1.51^{*}		0.94	
	Center (median)	0.65		1.97		2.02
	Spread (IQR)	1.86		2.82		1.67
G20	Asymmetry (MC)	0.61		0.08		0.00
(n=19)	Peakedness	1.54		1.23		2.14
	Multimodality (Dip)	0.066		0.066		0.092
	Spatial pool.	4.25^{***}		2.47^{***}		2.54^{***}
	Pair-wise time pool.		0.71		0.10	
	Center (median)	0.15		1.62		1.85
	Spread (IQR)	0.67		3.78		4.55
OPEC	Asymmetry (MC)	0.88		0.55		0.62
(n=11)	Peakedness	2.66		2.21		2.03
	Multimodality (Dip)	0.096		0.076		0.069
	Spatial pool.	-3.54		-0.06		-0.31
	Pair-wise time pool.		1.37^{*}		0.04	

Note: IQR and MC stand for interquartile range and medcouple respectively. * and ** indicate 5% and 10% rejection levels for the null of unimodality vs multimodality - Dip statistic of Hartigan and Hartigan (1985) - and for the null of distribution equality over time (time poolability) or with the 'rest of the world' (spatial poolability) - J_n statistic of Li (1996).

period 1960-2000, median emissions rise everywhere but dispersion drops in the EU15, OECD and G20 subsets. This brings the number of subsets that (sigma-) converge over the whole time horizon to four in this paper. By contrast, dispersion explodes in OPEC in that time interval. Regarding the early and late subperiods, we observe increasing median emissions and dispersion in OECD, G20 and OPEC but decreasing dispersion in EU15 between 1960 and 1980, while median emissions are stable and dispersion decreases in all subsets between 1980 and 2000 except in OPEC where both median emissions and spread keep rising.

The ergodic profiles shown on the right-hand-side plots in Figure 6 indicate that the 1960-2002 transition laws produce mainly flat density patterns and larger emissions compared to year 2000 for all political subsets. By contrast, the ergodic densities evaluated with 1980-2002 transitions are rather close to the spatial densities in 2000 for the EU15, OECD and G20 members and suggest further convergence (toward slightly larger emissions) for EU15, stable gaps and emissions for OECD, and a moderately polarized profile with 2 modes for the Group of Twenty. With respect to OPEC, larger emissions and gaps must be expected whatever the estimating period of the transition operator.

In sum, OPEC exhibits divergence and increasing median emissions since 1960 and the process is expected to continue in the future. The EU15, OECD and G20 groups display sigma-convergence over the whole (1960-2000) and late (1980-2000) periods, divergence (except for EU15) during the early period 1960-1980, and rising median emissions which stabilize after the oil shocks. Compared to the current distributions, the Markov analysis anticipates stable gaps and emissions for EU15 when transitions starting in 1960 (or 1970) are employed and further convergence toward slightly larger pollution levels when post-oil shock transitions are used. For the OECD and G20, the 1960-2000 dynamics favors more divergence and larger emissions in the future while the post-oil shock dynamics points toward stable gaps and emissions for the former subset and a moderate twin-peaks phenomenon (bipolarization) for the Group of Twenty.

6 Conclusion

This paper contributes to the existing empirical literature on convergence in carbon emissions across countries in several respects : (a) we expand the number of countries analyzed (166 world countries over the years 1960-2002), (b) we rely on both absolute and relative levels of per capita CO_2 emissions, (c) we explicitly test for multimodality in the distributions and poolability of a variety of country groupings with the rest of the world, and (d) we use robust distributional measures to characterize convergence, including a dynamic analysis based on Markov transition laws estimated over different time horizons which allow spatial distributions' forecasts.

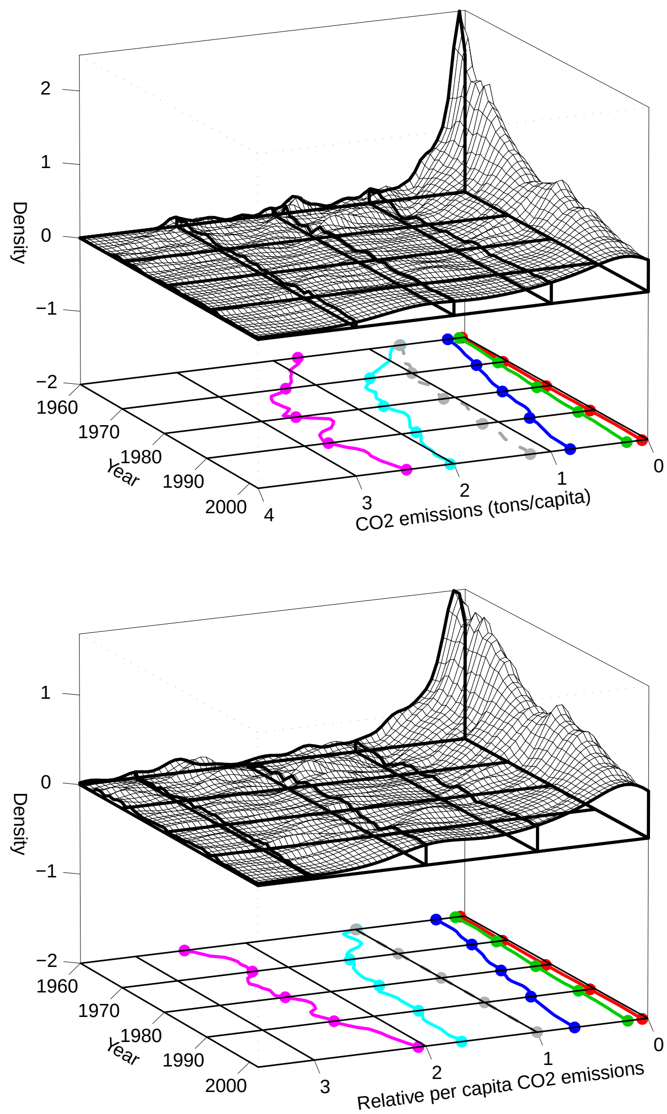
Our results indicate that convergence in the relative measure can be found in the presence of diverging and rising emissions in the unscaled data. Focusing on per capita emissions in levels, we highlight that strong divergence and increasing emissions are prevalent worldwide in the early period 1960-1980 but stabilization (in gaps and emissions) occurs after the oil price shocks of the 1970s. Significant differences between the successive world spatial distributions over time are detected in the early decades but not later on. The Markov analysis of the 166-country sample suggests bumpier and flatter ergodic densities with larger median emission levels compared to the distribution in year 2000, whatever the period used to estimate the transition law. This result points toward more divergence worldwide and larger per capita emissions that stabilize in the long run.

Grouping countries according to their income level, geographic proximity or systemic significance allows identification of clusters of converging economies. More specifically, four country subsets exhibit convergence (lower dispersion) across its members over the entire horizon 1960-2002 (Europe and Central Asia, OECD, EU15 and G20), a majority of groups display convergence throughout the late period 1980 to 2000 exclusively (high- and middle-income economies; Latin America & Caribbean, Middle-East and North Africa, Sub-Saharan Africa) and three groupings depict divergence over the full/early/late periods (East Asia and Pacific & South Asia, OPEC and the low-income countries to a lesser extent). None of the converging patterns is strong enough to generate multi-polarization in the world or group-specific distributions as multimodality is formally rejected over the whole period for all (sub)samples. Among the variety of group-specific ergodic density profiles, only Europe and Central Asia, Sub-Saharan Africa and the low-income countries possess unimodal and compact shapes, which suggest convergence toward lower emissions per capita in the long run, while those for OECD, EU15 and the G20 are close to their current distribution.

Overall, given that CO_2 emissions have not been penalized by stringent policy measures during the time span covered by the panel, these results indicate that, despite structural differences between countries, technical progress and price mechanisms favor a more efficient use of fossil fuels at the world level and in most regions that damp down the positive and diverging trends in per capita emissions characterizing the 1960s economic boom. Obviously, this does not mean that the stabilized (or 'steady state') pollution levels reached/anticipated are optimal from an environmental or economic point of view. Strong political action is required to avoid more divergence and larger per capita carbon emissions in the next decades. The existence of steady-state spatial distributions of per capita CO_2 emissions may support the emergence of fairer emission objectives for groups of economies and may help parties reach acceptable international compromises for post-Kyoto agreements.

7 Appendix

Figure 7: Cross-section densities of the world per capita CO_2 emissions without outliers (CDIAC128). Period 1960-2002.



Note: the red, green, navy blue, sky blue and magenta lines drawn on the floor represent respectively the 12.5%, 25%, 50%, 75% and 87.5% cross-sectional quantiles over time and are computed with a locally linear nonparametric quantile regressions. The grey dashed line is the cross-sectional arithmetic mean, slightly smoothed with a kernel regression. The univariate cross-sectional kernel densities are estimated with a Gaussian kernel and Zhang and Wang's (2009) robust normal reference bandwidth with $p \in (0.3, 0.5)$.

List of countries:[29] Afghanistan, Albania, Algeria, American Samoa, Angola, Antigua & Barbuda, Argentina, Australia, Austria, Bahamas, Bahrain, Bangladesh & Pakistan, Barbados, Belgium, Belize, Benin, Bermuda, Bolivia, Brazil, Brunei, Bulgaria, Burkina Faso, Cambodia, Cameroon, Canada, Cape Verde, Cayman Islands, Central African R., Chad, Chile, China, Colombia, Comoros, Congo (Rep.), Costa Rica, Côte d'Ivoire, Cuba, Cyprus, Czechoslovakia, Denmark, Djibouti, Dominica, Dominican R., Ecuador, Egypt, El Salvador, Equatorial Guinea, Ethiopia, Faeroe Islands, Fiji, Finland, France & Monaco, French Polynesia, French Guiana, Gabon, Gambia, Germany, Ghana, Gibraltar, Greece, Greenland, Grenada, Guadeloupe, Guam, Guatemala, Guinea, Guinea Bissau, Guyana, Haiti, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iraq, Iran, Ireland, Israel, Italy & San Marino, Jamaica, Japan, Jordan, Kenya, Korea (D.R.), Korea (R.), Kuwait, Laos, Lebanon, Liberia, Libya, Luxembourg, Macau, Madagascar, Malaysia, Mali, Malta, Martinique, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Netherlands, Neth. Antilles & Aruba, New Caledonia, New Zealand, Nicaragua, Niger, Nigeria, Norway, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Qatar, Reunion, Rhodesia-Nyasaland, Romania, Rwanda-Urundi, Samoa, Sao Tome & Principe, Saudi Arabia, Senegal, Sierra Leone, Singapore, Solomon Islands, South Africa, Spain, Sri Lanka, St. Lucia, St. Pierre & Miquelon, St. Vincent & Grenada, Suriname, Sudan, Sweden, Switzerland, Syria, Taiwan, Tanzania, Thailand, Togo, Tonga, Trinidad. & Tobago, Tunisia, Turkey, Uganda, United Arab Em., United Kingdom, Uruguay, USA, USSR, Venezuela, Vietnam, Virgin Islands (US), Yemen, Yugoslavia, Zaire.

Acknowledgments

Preliminary results for this paper were presented at the EAERE 2009 Meeting in Amsterdam (Holland), at SURED 2008, in Ascona (Switzerland) and at the Conference on Growth and Human Capital, May 2007, Guelph, Canada. We also benefited from helpful comments from Jim de Melo and Scott Taylor. We thank David Goldblatt for his careful linguistic check. Financial help from the Swiss National Science Foundation under grants No 100012-109926 and No 100012-117872 is gratefully acknowledged. The usual disclaimer applies.

[29] Underlined countries are those with annual growth rates in per capita carbon emissions more than doubling/halving for at least one of the years of the period 1960-2002.

References

Aldy, J.E., "Per Capita Carbon Dioxide Emissions: Convergence or Divergence," *Environmental and Resource Economics*, 2006, *33*, 533–555.

__ , "Divergence in State-Level Per Capita Carbon Dioxide Emissions,," *Land Economics*, 2007, *83(3)*, 353–369.

Arrellano, M. and S. Bond, "Some tests of Specification for Panel Data: Monte-Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 1991, *58*, 277–297.

Barrasi, M.R., M.A. Cole, and R.J.R. Elliott, "Stochastic Divergence or Convergence of Per Capita Carbon Dioxide Emissions: Re-examining the Evidence," *Environmental and Resource Economics*, 2008, *40(1)*, 121–137.

Barro, R.J. and X. Sala i Martin, *Economic Growth*, second ed., Massachusetts: The MIT Press, 2004.

Bernard, A.B. and S. Durlauf, "Convergence in international output," *Journal of Applied Econometrics*, 1995, *10*, 97–108.

Bianchi, M., "Testing for Convergence: Evidence from Nonparametric Multimodality," *Journal of Applied Econometrics*, 1997, *12*, 393–409.

Bodansky, D., S. Chou, and C. Jorge-Tresoni, "International Climate Efforts beyond 2012: a Survey of Approaches," Working paper, Pew Center on Global Climate Change December 2004.

Brock, W.A. and M.S. Taylor, "The Green Solow Model," Working paper 10557, NBER June 2004.

Brys, G., M. Hubert, and A. Struyf, "A Robust Measure of Skewness," *Journal of Computational and Graphical Statistics*, 2004, *53* (4), 996–1017.

__ , __ , and __ , "Robust Measures of tail weight," *Computational Statistics and Data Analysis*, 2006, *50*, 733–759.

Carlino, G.A. and L.O. Mills, "Are US regional incomes converging?," *Journal of Monetary Economics*, 1993, *32*, 335–346.

Copeland, B.R. and M.S. Taylor, "Free trade and global warming: a trade theory view of the Kyoto protocol," *Journal of Environmental Economics and Management*, 2005, pp. 205–234.

Davison, A.C. and D.V. Hinkley, *Bootstrap Methods and their Applications*, 1st ed., Cambridge Series in Statistical and Probabilistic Mathematics, 1997.

Durlauf, S.N., P.A. Johnson, and J.R.W. Temple, "Growth Econometrics," in S.N. Durlauf and P. Aghion, eds., *Handbook of Economic Growth*, Elsevier 2005, p. Ch.8.

Evans, P., "Using panel data to evaluate growth theories," *International Economic Review*, 1998, *39(2)*, 295–306.

Ezcurra, R., "Is there cross-country convergence in carbon dioxide emissions," *Energy Policy*, 2007, *35*, 1363–1372.

Hartigan, J.A. and P.M. Hartigan, "The Dip Test of Unimodality," *The Annals of Statistics*, 1985, *13* (1), 70–84.

Hayfield, Tristen and Jeffrey S. Racine, "Nonparametric Econometrics: The np Package," *Journal of Statistical Software*, 2008, *27* (5).

Heil, M.T. and T.M. Selden, "Panel stationarity with structural breaks: carbon emissions and GDP," *Applied Economics Letters*, 1999, *6*, 223–225.

Henderson, Daniel J., Christopher F. Parmeter, and R. Robert Russell, "Modes, weighted modes, and calibrated modes: evidence of clustering using modality tests," *Journal of Applied Econometrics*, 2008, *23* (5), 607–638.

Im, K.S., M.H. Pesaran, and Y. Shin, "Testing for unit root in heterogeneous panels," *Journal of Econometrics*, 2003, *115*, 53–74.

Johnson, P.A., "A Nonparametric Analysis of Income Convergence across the U.S. States," *Economics Letters*, 2000, *69*, 219–223.

Koenker, Roger, *quantreg: Quantile Regression* 2009. R package version 4.44.

Komsta, L. and F. Novomestky, *moments: Moments, cumulants, skewness, kurtosis and related tests* 2007. R package version 0.11.

Lanne, M. and M. Liski, "Trends and Breaks in Per-Capita Carbon Dioxide Emissions, 1870-2028," *The Energy Journal*, 2004, *25* (4), 41–66.

Li, Q., "Nonparametric testing of closeness between two unknown distribution functions," *Econometric Reviews*, 1996, *15* (3), 261–274.

Lumley, T. and M. Maechler, *adapt – multidimensional numerical integration* 2007. R package version 1.0-4. Adapted from FORTRAN code by Alan Genz and S code by Mike Meyer.

Maechler, M. and D. Ringach, *diptest: Hartigan's dip test statistic for unimodality - corrected code* 2009. R package version 0.25-2, based on Fortran and Splus from Dario Ringach (NYU.edu).

Marland, G., T.A. Boden, and R.J. Andres, "Global, Regional, and National Fossil Fuel CO_2 Emissions," In: Trends: A Compendium of Data on Global Change, Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Dpt. of Energy, Tenn., U.S.A. 2006. `http://cdiac.ornl.gov/trends/emis/tre_coun.htm`, June.

McKitrick, R. and M.C. Strazicich, "Stationarity of Global Per Capita Carbon Dioxide Emissions: Implications for Global Warming Scenarios," Working Paper 2005-03, University of Guelph 2005.

Pagan, A. and A. Ullah, *Nonparametric Econometrics*, first ed., USA: Cambridge University Press, 1999.

Panopoulou, E. and T. Pantelidis, "Club Convergence in Carbon Dioxide Emissions," *Environmental and Resource Economics*, 2009, *44(1).*

Pesaran, M.H., "A pair-wise approach to testing output and growth convergence," *Journal of Econometrics*, 2007, *138.*

Phillips, P.C.B. and D. Sul, "Transition modeling and econometric convergence tests," *Econometrica*, 2007, *75.*

Quah, D., "Empirical cross-sectional dynamics in economic growth," *European Economic Review*, 1993, *37*, 426–434.

__ , "Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs," *Journal of Economic Growth*, 1997, *2*, 27–59.

R Development Core Team, *R: A Language and Environment for Statistical Computing* R Foundation for Statistical Computing 2009. ISBN 3-900051-07-0.

Romero-Ávila, D., "Convergence in carbon dioxide emissions among

industrialised countries revisited," *Energy Economics*, 2008, *30*, 2265–2282.
Rose, A., S. Brandt, J. Edmonds, and W. Marshall, "International Equity and Differentiation in Global Warming Policy," *Environmental and Resource Economics*, 1998, *12*, 25–51.
Schmid, F. and M. Trede, "Simple test for peakedness, fat tails and leptokurtosis based on quantiles," *Computational and Data Analysis*, 2003, *43*, 1–12.
Silverman, B.W., *Density estimation for statistics and data analysis*, London: Chapman and Hall, 1986.
Stegman, A., "Convergence in Carbon Emissions per Capita," Working paper 8, CAMA, The Australian National University 2005.
Strazicich, M.C. and J.A. List, "Are CO_2 Emissions Levels Converging Among Industrial Countries?," *Environmental and Resource Economics*, 2003, *24*, 263–271.
U.S. Census Bureau, "International Data Base (IDB)," Online data, Population Division, International Program Center, 2006. http://www.census.gov/ipc/www/idb/.
Van, P. Nguyen, "Distribution Dynamics of CO_2 Emissions," *Environmental and Resource Economics*, 2005, *32*.
Westerlund, J. and S.A. Basher, "Testing the Convergence in Carbon Dioxide Emissions Using a Century of Panel Data," *Environmental and Resource Economics*, 2008, *40*, 109–120.
World Bank, "World Development Indicators," CD-rom, Washington DC, USA 2004.
Zhang, J. and X. Wang, "Robust normal reference bandwidth for kernel density estimation," *Statistica Neerlandica*, 2009, *63* (1), 13–23.