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Alison Stegman
Macquarie University

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Alison Stegman*[#]

ABSTRACT

Convergence in cross country per capita carbon emission rates is an important concept in the climate change debate. This paper provides an empirical analysis of emissions per capita convergence. This analysis is crucial to the assessment of projection models that generate convergence in emission per capita rates and to the assessment of policy proposals that advocate imposing convergence in emissions per capita. The main conclusions in this paper are based on a detailed examination of the intra-distributional dynamics of cross country emissions per capita over time. Stochastic kernel estimation of these dynamics suggests that the cross country distribution of emissions per capita is characterised by persistence. There is little evidence that emission per capita rates across countries are converging in an absolute sense. Projection models that generate convergence in emissions per capita are therefore inconsistent with empirical behaviour. Policies that impose convergence in emissions per capita are likely to generate large re-distributional impacts.

JEL Classification: C10, C14, Q54

Keywords: emissions, distribution dynamics, convergence, stochastic kernel

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[#] Department of Economics, Division of Economic and Financial Studies, Macquarie University, NSW Australia 2109. Email: astegman@efs.mq.edu.au

1. Introduction

Climate change represents a significant and complex challenge to policy makers. Economic analysis is crucial to the climate policy debate. Continued research into climate change and appropriate policy action is necessary if governments are going to adopt an efficient and effective response. This paper highlights the important role of economics in the climate change debate by analysing the role of convergence assumptions in generating emissions projections and in generating policy proposals. By imposing convergence conditions in a projection model, differences between countries, in either a specific key variable or in a range of variables, are assumed to narrow over time. Assessing the methodology used to project future emissions is critical to the climate change debate because projections of future emissions are central to the debate over an appropriate climate policy response. Projections should help to reduce the uncertainty surrounding climate change by providing information on the possible costs across countries in the absence of any climate policy response and by providing a framework in which to analyse alternative policy options. To be relevant projection models should take account of the aggregate trends and the distributional dynamics observed in key model variables.

This paper provides an analysis of the evolution of carbon emissions per capita over time. The key question is whether emissions per capita show any evidence of convergence, as is assumed in many climate projection models. A clear understanding of the distribution of emissions per capita and the evolution of this distribution over time is crucial to the development of relevant emissions projection models and appropriate policy responses.

Policy proposals designed to address the issue of climate change must consider the empirical behaviour of key target variables if they are going to be practical and appropriate. Policy proposals that advocate imposing convergence in emissions per capita are likely to involve large distributional impacts if there is no natural tendency towards convergence across countries.

2. Theoretical Issues

The debate over emissions per capita convergence assumptions and the existence of policy proposals that advocate the distribution of emission permits on an equal per capita basis suggests that convergence in emissions per capita is a phenomenon that researchers regard as either a possibility or as a desirable outcome that should be the basis of policy.

From an economic point of view, a desirable distribution of emissions across countries is an *efficient* distribution, where an efficient distribution is defined as an allocation that maximises the value of resources (where marginal benefits equal marginal costs). Most climate change policy proposals include some variation of a tradable permit system that ensures, under certain conditions, an efficient distribution regardless of the initial allocation of permits. It is possible (although unlikely) that an efficient allocation will be one where emission per capita rates are equal across countries. However, before imposing such a distribution on emissions, it would be important to investigate the properties and effects of such a policy.

Policy proposals that advocate convergence in emission per capita rates have emphasised the social value of such a distribution, drawing heavily on ideas of 'fairness' and 'equity'. The Global Commons Institute (GCI) argues that "emissions need to be allocated by countries in a way that is both achievable and is seen by all to be fair" (GCI, 1998). If greenhouse gas emissions result primarily from individual activities such as the use of automobiles and private electricity consumption then the idea of allocating each individual the same 'right to pollute' may appeal to some notion of fairness. However, the distribution of fossil fuel related carbon dioxide (CO_2) emissions[1] is strongly related to the structure of a country's economy, which in turn depends on that country's natural endowments, development level and its comparative advantage in the production of various goods. Given the (possibly large) wealth transfers that could result from changing the distribution of emissions across countries, it is not clear that imposing convergence in emission per capita rates would be fair or equitable.

[1] Carbon dioxide is considered the most important human influenced greenhouse gas for climate analyses and policy targeting because it accounts for around two-thirds of greenhouse gas radiative forcing (the enhancement of the greenhouse effect) and because it is relatively easy to monitor. Fossil fuels account for around three quarters of anthropogenic CO_2 emissions. (IPCC, 2001)

From an environmental point of view, the global nature of the climate change problem suggests that it is the total world level of emissions that matters the most, rather than the distribution of these emissions across country borders. Nevertheless, the features of a particular policy proposal will impact how successful it is and whether or not it is accepted by the majority of countries. If the requirement that countries equate their emission per capita rates results in a significant redistribution of emissions across countries, then the costs for some countries could be large.

It is important therefore, when formulating such policy proposals, to understand the current distribution of emissions and how a particular policy proposal is likely to affect this distribution. The examination in this paper, therefore, is fundamental to the policy debate.

3. Literature Review

Given that there has been extensive debate over convergence emissions policies and emission permit allocations determined on a per capita basis, the literature that empirically considers the tendency towards convergence in emissions per capita is very limited. Heil and Woden (1999) use decompositions of the Gini Index (a measure of inequality) to analyse convergence in projected emissions per capita out to 2100. The distribution of emissions in the analysis is, however, driven by assumptions in the forecasting model, such as convergence in GDP per capita and a diminishing marginal propensity to emit per capita. The conclusion that "convergence in per capita emissions is indeed likely" (p23) must therefore be interpreted with caution. The forecasting model used in the study is based on an econometric estimation of key economic variables but the model is still driven to a large extent by the underlying assumptions and the conclusions regarding convergence must be viewed as conclusions relating to this model specification.

The most comprehensive empirical studies of convergence in emissions per capita have taken a time series or common trends approach to convergence analysis. Bernard and Durlauf (1995, 1996) have used this approach to analyse and test for convergence in international output. Bernard and Durlauf use tests for cointegration to examine the existence of *stochastic convergence* and common trends in international output.

Strazicich and List (2003) use the approach to examine stochastic convergence in emissions per capita by applying panel unit root tests to the emissions per capita from 21 industrialised countries over the period 1960 to 1997. The basic idea is to calculate the variable $\ln(CO_2pc_{it}/CO_2pc_t)$ (which is the log ratio of carbon dioxide emissions per capita in country i to the average emissions per capita rate for the sample) for each country and test for unit roots. The regression test specifications include a country specific constant term, or compensating differential and a time trend and the test for convergence is therefore a test of *stochastic conditional convergence* or common trends rather than a test for absolute convergence. In a test for absolute convergence both the constant term and the time trend coefficient would be restricted to zero. Strazicich and List reject the null hypothesis of a unit root in their test and therefore find evidence of stochastic conditional convergence in emissions per capita. This result must be evaluated with reference to the definition of convergence used and the series under consideration.

Under the stochastic conditional convergence definition, shocks to the emissions per capita of individual countries relative to the average level of emissions per capita are temporary. The implication of this behaviour for absolute convergence depends on the model specification.

Consider the following model specifications used to test for unit roots:

$$\Delta y_t = \gamma y_{t-1} + e_t \qquad (1)$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + e_t \qquad (2)$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + e_t \qquad (3)$$

Rejection of the unit root hypothesis ($\gamma = 0$) in specifications (2) and (3) implies that the series y_t is stationary around a constant and stationary around a constant and a trend, respectively. If $y_t = \ln(CO_2pc_{it}/CO_2pc_t)$, then absolute convergence in emissions per capita requires that both a_0 and a_2 are equal to zero. If either a_0 or a_2 are non zero, there is a predictable gap between emissions per capita in any particular country and the average emissions per capita rate.

The Strazicich and List analysis is restricted to a sample of 21 industrialised countries. In the growth literature the use of such a restrictive sample implies a conditional convergence analysis because the countries under consideration are likely to share similar steady state characteristics. The framework presented by Bernard and Durlauf (1996) however, suggests that this type of data set is the most suitable to time series studies of convergence. They argue that time series tests of convergence assume that the data possess well defined population moments and that inferences from the time series approach may be invalid when based on data that are far from the limiting distribution. This suggests that the time series approach to convergence analysis may be most appropriate for industrialised countries that are most likely to be characterised by steady state behaviour. Bernard and Durlauf (1996) suggest that an alternative cross-sectional approach to convergence analysis would be appropriate for a data set characterised by transitional dynamics.

Using a specification that includes both a constant and a time trend, Strazicich and List reject the hypothesis of a unit root using the IPS Panel Unit Root Test (Im, Pesaran and Shin, 2003) and conclude that "the null hypothesis that emissions have diverged is strongly rejected". They argue that their results provide significant evidence that cross-country per capita CO_2 emissions have converged. As outlined above, the analysis examines conditional convergence through a number of restrictions, on the sample set under consideration and the test regression specifications. The analysis does not provide support for unconditional or absolute convergence of cross country emissions per capita. The existence of unconditional or absolute convergence is the focus of the empirical analysis undertaken in this paper. The conditional analysis presented in Strazicich and List (2003) is, however, still useful to researchers interested in modelling and projecting emissions. Evidence that there is a predictable relationship between emission per capita rates across countries could be integrated into long term models of future emission levels.

An analysis of unconditional convergence is however crucial to the assessment of policy proposals that advocate imposing convergence in emissions per capita and to the assessment of emission projection models that include convergence assumptions.

4. Measuring Convergence

Studies of convergence in the growth literature have tended to consider two alternative definitions of convergence: beta convergence and sigma convergence. Beta convergence refers to the existence of a negative relationship between the growth rate of income per capita (or the variable of interest) and the initial level – a situation where poor countries tend to grow faster than richer countries. The implication is that poor countries will eventually 'catch-up' to the income levels of richer countries. Papers by Sala-i-Martin (see, for example, 1996a, 1996b, 2002) and Barro and Sala-i-Martin (1991, 1992) have been particularly influential.

Sigma convergence refers to a reduction in the spread or dispersion of a data set over time. Beta convergence is a necessary condition for sigma convergence, but it is not a sufficient one (Quah (1995a) and Sala-i-Martin (1996b) provide a formal algebraic derivation of this result). Some researchers have argued the relative merits of the beta and sigma approaches to convergence analysis (see, for example, Quah (1995a)). Sala-i-Martin, however, argues that "the two concepts examine interesting phenomena which are conceptually different … both concepts should be studied and applied empirically" (pp 1328-1329, 1996b).

A third approach to convergence analysis is the commons trends or time series approach discussed in the previous section. The times series approach to convergence analysis is based on the assumption that forecasts of variable differences converge to zero in expected value as the forecast horizon becomes arbitrarily long. If the differences between countries' variable levels contains either a non zero mean or a unit root then the convergence condition is violated (Bernard and Durlauf, 1995, 1996).

The main results of this paper are based on a dynamic distributional approach to convergence analysis. The distributional approach to convergence analysis was developed in a series of papers by Quah (see 1995a, 1995b, 1996, 1997, 2000). Quah (1995a) argues that cross sectional regression approaches to convergence (the estimation of beta convergence) analyse "only average behaviour" (p 15) and are uninformative on a distribution's dynamics because they "only capture 'representative' economy dynamics" (p 16). Quah argues that "to address questions of catch-up and convergence, one needs to model explicitly the dynamics of the entire cross-country distribution" (1995b, p1). He proposes a dynamic distributional approach to convergence analysis and applies his techniques to a number of alternative theoretical specifications. Quah's approach has been influential because it has applications in a wide range of research areas (see Overman and Puga (2002) for an application to regional unemployment).

The dynamic distributional approach to convergence considers the existence of sigma convergence but provides a more detailed examination of the dynamic intra-distributional properties of the data set. As explained in Section 6 below, the dynamic distributional approach does not restrict convergence analysis to a single characteristic of the data. It seeks to examine the full dynamic nature of the cross-country distribution of the variable of interest and is particularly valuable for considering the evolution of non-normal distributions.

5. Descriptive Data Analysis

5.1 The Data

The data used in this paper are from two main sources. National data on fossil fuel CO_2 emissions and CO_2 emissions per capita are sourced from Marland et al (2003). The data relates to carbon dioxide emissions from the consumption of fossil fuels but is generally referred to as emissions throughout the paper (see footnote 1). Historical estimates of population prior to 1950 were obtained from Maddison (1995, 2003). It is possible to disaggregate the data on fossil fuel CO_2 emissions into emissions from five sources: solid (mainly coal) fuel consumption, liquid (mainly petroleum) fuel consumption, gas fuel consumption, cement production, and gas flaring. Total fossil fuel CO_2 emissions from all sources are considered in this paper.

5.2 World Trends (Marland et al, 2003)

In 2000, world fossil fuel emissions were estimated at 6611 million metric tons of carbon. Liquid and solid fuels accounted for 77 percent of the total, the combustion of gas fuels accounted for 19 percent, 3 percent was attributed to cement production and less than 1 percent was the result of gas flaring. The global per capita emissions rate in 2000 was 1.1

metric tons. This rate has been relatively stable since the 1970s. Growth in fossil fuel emissions was generally strong over the 1950s, 1960s and 1970s. Since then, emissions have continued to grow, although the rate of growth has not been consistently as high (Figure 1). In particular, the oil price shocks of the 1970s affected emissions in the early 1980s.

The top 5 sources for emissions, in 2000, in order, were: the United States, China, Russia, Japan and India (Figure 2). Australia ranked fourteenth. These trends are outlined in more detail below.

5.3 National Trends (Marland et al 2003)

The United States is the largest source of fossil fuel related CO_2 emissions. In 2000, fossil fuel emissions from the United States reached 1529 million metric tons of carbon, twice as high as the second highest emitter, the People's Republic of China. The United States' share of emissions in total world emissions, however, is estimated to have fallen from over 40 percent in 1950 to 23 percent in 2000. The United States' per capita emissions rate in 2000 was a relatively high 5.4 metric tons of carbon.

China is the world's second largest source of CO_2 emissions. China is the world's largest producer, and the second largest exporter, of coal and coal consumption accounts for almost 70 percent of China's total CO_2 emissions. China is also the world's largest hydraulic cement producer and cement production accounted for around 10 percent of China's total emissions in 2000. With a large population, China's per capita emission rate was a relatively low 0.6 metric tons of carbon in 1999.

Russia is the world's third largest source of fossil fuel CO_2 emissions. However, Russia's estimated 2000 total of 392 million tons of carbon, represents a fall of 28 percent since 1992. Russia is the world's largest producer of natural gas and half of Russia's CO_2 emissions are the result of gas consumption. Estimates of Russian CO_2 emissions are only available from 1992 onwards and, as such, Russia is omitted from the statistical analyses conducted in this paper.

Japan is the fourth largest source of fossil fuel CO_2 emissions, estimated to be 323 million tons of carbon in 2000. Japan is the largest importer of coal and liquefied petroleum gas, the second largest importer of crude oil and the second largest importer of natural gas. Japan's per capita fossil fuel CO_2 rate was 2.55 metric tons in 2000.

India is the world's fifth largest source of fossil fuel CO_2 emissions with an estimated 292 million metric tons of carbon emissions in 2000. India is the world's third largest coal producer and most (over 70 percent) of India's emissions are the result of coal burning. With the world's second largest population, India's 1999 per capita emission rate was a relatively low 0.29 metric tons.

Australia is the fourteenth largest source of fossil fuel CO_2 emissions, with an estimated 94 million metric tons of carbon emissions in 2000. Australia is the world's fourth largest coal producer and the largest exporter of coal. Coal consumption accounts for almost 60 percent of Australia's 2000 emissions total. Australia's per capita emission rate in 2000 was a relatively high 4.91 metric tons of carbon.

6. Econometric Analysis

The analysis undertaken in this section is designed to provide a comprehensive and dynamic examination of the cross-country distribution of fossil fuel CO_2 emissions. The information presented in this section provides an empirical foundation for projecting emissions and the analysis undertaken provides general information on the distribution of fossil fuel CO_2 emissions and how this distribution has changed over time. The analysis is not restricted to a single characteristic of the data – it seeks to examine the full dynamic nature of the cross-country distribution of emissions per capita. The analysis is structured to answer the question: do emission per capita rates across countries converge over time? With normally distributed data, convergence could be defined as a reduction in the dispersion or spread of a data set. This definition is often referred to as 'sigma convergence' in the growth literature. With data that is not normally distributed, however, this definition is likely to be inappropriate, particularly if the data set exhibits multiple peaks. The standard summary statistics that attempt to measure dispersion implicitly assume a narrow definition of convergence and are, as such, uninformative on more complicated dynamic behaviour. For this reason, convergence in emissions per capita is assessed by examining a variety of summary measures and through a comprehensive dynamic analysis of the entire cross-country distribution of fossil fuel CO_2 emissions. A range of stochastic kernels that describe how the cross-county distribution of emissions per capita at time t evolves into the distribution at time $t+k$ are estimated to examine these dynamics.

6.1 Sample Definitions

The main data set used in this section is Sample A. It includes 97 countries over the period 1950 to 1999 (see Table 1). In addition, some results for a set of countries for which data is available over a longer time frame (Sample B) are provided. Unfortunately the number of countries in Sample B is significantly reduced. Sample B includes 26 countries over the period 1900 to 1999 (these are highlighted with an asterisk (*) in Table 1).

All OPEC countries are excluded from the analysis. These countries have highly variable emissions series and, as such, have a disproportionately large effect on aggregate statistics, such as those used in this analysis.

6.2 Summary Measures

A variety of summary statistics are used to measure the spread or variability of a data set (NIST/SEMATECH, 2003). Six measures are considered here: the variance (VAR), the standard deviation (STDEV), the coefficient of variation (CV), the average absolute deviation (AAD), the median absolute deviation (MAD), and the interquartile range (IQR).

The (sample) variance of a data set is defined as

$$VAR = \frac{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}{(N-1)} \qquad (4)$$

where $\bar{Y}$ is the mean of the data set and Y_i is the data under consideration.

The variance uses the squared difference from the mean, giving greater weight to values that are further from the mean. The variance, therefore, can be strongly affected by the behaviour in the tails of a distribution.

The (sample) standard deviation of a data set is defined as

$$STDEV = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \bar{Y}\right)^2}{(N-1)}} = \sqrt{VAR} \tag{5}$$

When comparing the standard deviation of two data sets or over two points in time, researchers often normalise the standard deviation by dividing by the mean of the data. This statistic is called the coefficient of variation and is defined as

$$CV = \frac{STDEV}{MEAN} \tag{6}$$

The coefficient of variation can be used to compare variation in data sets with different means and to compare changes in the spread of a data set over time.

The average absolute deviation is defined as

$$AAD = \frac{\sum_{i=1}^{n}\left(\left|Y_i - \bar{Y}\right|\right)}{N} \tag{7}$$

where $|Y|$ is the absolute value of Y.

The AAD does not square the distance from the mean and it is therefore less affected than the variance by extreme observations.

The median absolute deviation is defined as

$$MAD = median\left(\left|Y_i - \tilde{Y}\right|\right) \tag{8}$$

where $\tilde{Y}$ is the median of the data.

The MAD is even less affected by extreme observations in the tails of the distribution of the data.

The interquartile range (IQR) is the value of the 75th percentile minus the value of the 25th percentile. The IQR attempts to measure variability in the centre of the distribution and does not, therefore, consider tail behaviour.

All of the above statistics, except for the IQR, attempt to measure variability, both around the centre and in the tails of a distribution. They differ in the weight placed on observations in the tails (NIST/SEMATECH, 2003). The appropriate statistic will depend upon the question of interest and the distribution of the data under consideration.

With a normally distributed data set, the variance or the standard deviation provide the best representation of the spread of the data set, both around the centre and in the tails. With data that is not normally distributed, however, an alternative method, such as the median absolute deviation or the average absolute deviation, may be more appropriate.

Figures 3 and 4 contain estimates of each of these measures for Sample A over the period 1950 to 1999. In Figure 3, the mean along with the variance, the standard deviation and the coefficient of variation are plotted. Both the mean and the standard deviation of the data set increase over the sample period. Between 1950 and 1999, the mean increases by more than the standard deviation (which increases only slightly) and, as a result, the coefficient of variation is falling over this period. Both the average absolute deviation and the median absolute deviation of Sample A increase over the period 1950 to 1999. The interquartile range, which only looks at the spread in the centre of the distribution, is also increasing over the time period (Figure 4).

In summary, all of the measures, except for the coefficient of variation, increase over the period 1950 to 1999. This suggests that the spread or variability of the data series, emissions per capita, increased over the period from 1950 to 1999. These summary statistics are not consistent with a series that exhibits convergence.

The CV result highlights the inconsistency between alternative measures of spread. A researcher who restricted their analysis to the coefficient of variation may conclude that the variation or spread in cross-country emissions per capita declined over the period 1950 to 1999.

6.3 Distributional Analysis

Convergence is a difficult concept to define. In the context of a distributional analysis, convergence could be defined as a sequence of distributions collapsing over time to a point limit (Quah, 1997). Progress in this area would then depend upon the series under consideration. For example, the previous statistical analysis looked at the distribution of *emissions per capita*. Using this series in a distributional analysis would implicitly define convergence in terms of the differences in *levels* between countries' emission per capita rates.

An alternative approach might look at the distribution of countries' emission per capita rates relative to the world average. This allows the analysis to abstract from the general increase in emission per capita rates over time. The definition of convergence now concentrates on *proportional* deviations from the mean. When the mean is changing over time, convergence to a particular emissions per capita rate is not distinguished from the convergence of countries to a per capita emissions rate that changes over time.

Lastly, the logarithm of emissions per capita rates could be examined so that the definition of convergence depends on the *percentage* deviation between countries.

Analyses that seek to study convergence must therefore clearly define convergence and how it relates to the series under consideration. The analysis in this section considers relative emissions per capita, where emissions are measured as both the levels deviation from the mean and the proportional deviation from the mean. These series are the most appropriate for an analysis of emissions and the most relevant to the current research debate.

This section utilises cross country density estimation techniques developed by Quah (1995a, 1995b, 1997) to study income convergence. Kernel-smoothed estimates of the cross-country density of fossil fuel CO_2 emissions over time are plotted. The estimates were obtained using the Kernel Estimator described in Pagan and Ullah (1999, p 9).

The estimator is defined as

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{9}$$

where x_i is the data under consideration;

the kernel $K(\cdot)$ is the standard normal;

the window width, $h = 2*\min(\sigma, (R/1.34))n^{-1/5}$, where R is the interquartile range; and

n is the sample size.

In Figures 5, 6 and 7, kernel-smoothed cross-country densities for fossil fuel CO_2 emissions per capita are presented. In Figure 5 cross-country density estimates for various years between 1950 and 1999 – the time period over which the most comprehensive data set is available (Sample A) – are plotted. A general interpretation of the density functions based on Sample A is one of divergence. Although the 1950 density function exhibits more than one peak, the majority of countries are clearly grouped around 0.1 metric tons of carbon per capita. In 1999, there is no apparent peak. The majority of countries lie in the relatively wide range from 0.1 to 2.5 metric tons of carbon per capita. Both the mean and the variance of this data set would have increased over this time period (this is confirmed by the summary statistics previously provided). A visual interpretation of the distributions suggests that between 1950 and 1999, the distribution of emissions per capita changed significantly, with an increase in the mean and the variance and a flattening of the entire distribution.

In Figure 6, the nonparametric densities for Sample B are plotted. From 1900 to 1990, there is a flattening of the distribution which appears consistent with divergence in emissions per capita rates. Over the decade from 1990 to 1999, the density appears to narrow slightly in the middle. Given that the number of countries in Sample B is relatively small, and that, as with income distribution analyses, there may be some selection bias due to data availability, these results are not inconsistent with the conclusions based on Sample A. This does, however, highlight the need for a more detailed examination of the intra-distribution dynamics.

Figure 7 contains density estimates for relative emissions per capita rates based on Sample A. The data under consideration are the emission per capita rates for each country at time t, divided by the cross country average emissions per capita rate at time t. A 2 on the x-axis therefore represents 2 times the cross-country average. The results are similar to those presented in Figure 5. The interesting differences are less flattening in the distribution over time and a substantial change in the range of the distribution over time. The reduction in the range of the data set helps to explain why the coefficient of variation for the original data set (Figure 3), which is the standard deviation for this relative data set, decreases over time.

Plotting the cross-country density over time provides information on how the *shape* of the distribution is evolving. Density plots do not provide information on the intra distributional dynamics of the data set. For example, two data sets may both be characterised by density plots that do not appear to change over time. One data set is characterised by a high level of persistence, whilst the other is characterised by a high degree of mobility. This distinction is not gained from an examination of density plots but the intra-distributional dynamic properties of a data set are an important feature of the data that needs to be considered in projection models and policy approaches.

A data series with a distribution that exhibits a high degree of mobility is more likely to be responsive to a policy proposal that imposes convergence than a distribution that exhibits a high degree of persistence. The distinction is also important when considering projection model assumptions since a data distribution that is characterised by persistence would be driven by very different factors from one characterised by a high degree of mobility. In the case of emissions per capita, for example, a high level of persistence would highlight the importance of country specific factors such as fossil fuel endowments and it would suggest that imposing an alternative distribution on emissions per capita may be difficult and costly.

The next step in the analysis of emissions per capita therefore involves estimating the intra-distributional dynamics. The stochastic kernel used to estimate these dynamics is based on the details in Quah (1995b). Readers interested in a more technical (and theoretical) derivation are directed towards the explanation provided in Quah (1997).

The calculation of the stochastic kernel estimates is similar to the calculation of a non parametric conditional density function:

$$\hat{f}\left(x_{t+k} \mid x_t\right) = \frac{\frac{1}{nh^2}\sum_{i=1}^{n} K_1\left(\frac{\left(x_{t+k,i}, x_{t,i}\right) - \left(x_{t+k}, x_t\right)}{h}\right)}{\frac{1}{nh}\sum_{i=1}^{n} K_1\left(\frac{x_{t,i} - x_t}{h}\right)} \tag{10}$$

where $x_{t,i}$ is the data under consideration at time period t

$x_{t+k,i}$ is the data under consideration at time period $t+k$

the kernel $K_1(\cdot)$ is the Epanechnikov; $h = 3*n^{-1/6}$

Rather than use a kernel estimate as the denominator (as is done in Equation 10), the denominator used in this analysis is calculated by numerically integrating under the joint density function (the numerator). This ensures that the integral from any point x_t across x_{t+k} is unity (see interpretation below).[2]

Readers unfamiliar with these calculations can think of the stochastic kernel estimates as a continuous representation of a transition probability matrix.

When analysing the convergence properties of a data set, it is important to account for movements in the average rate of emissions per capita. The relative series considered above is one method of doing so. However, as is clear from a comparison of Figures 5 and 7, such a transformation may affect the conclusions drawn. In this dynamic analysis of emissions per capita, the concept of convergence in both levels and in proportions to the mean is considered. Two data transformations are used.

Firstly, a *relative emissions per capita* series is considered where each country's emission per capita rate is at time *t* is divided by the cross-country sample average emission per capita rate at time *t*. This series measures proportional deviations from the cross-country mean.

Secondly, a *levels relative emissions per capita* series is considered where the cross-country sample average emission per capita rate at time *t* is subtracted from each country's emission per capita rate at time *t.* This series measures level deviations from the mean.

[2] Pagan and Ullah (1999) note that whilst kernel based density estimates are not very sensitive to the choice of kernel, they are sensitive to the choice of window width, *h*. For this reason alternative values of *h* were investigated. Smaller values of *h* do not qualitatively change the results or the conclusions presented here but they do make estimation difficult in areas of the distribution where observations are limited. As noted below, readers should be careful when interpreted the results for parts of the distribution where observations are limited.

In Figures 8 and 10 the conditional densities based on these series are plotted. Figures 9 and 11 contain the corresponding contour graphs. In both cases, the time period over which transitions are measured is 10 years.

Interpreting these graphs is relatively simple. From any point on the axis marked *Period t*, extending parallel to the axis marked *Period t+10*, the stochastic kernel is a probability density function (Quah, 1997). It describes transitions over 10 years from a given emissions per capita rate in period *t*. A ridge along the 45° line extending from the bottom left hand corner indicates a high degree of persistence – countries with a given (relative) emissions per capita rate in period *t* are likely to remain at that rate in period *t+10*. A ridge extending from any point in the axis marked *Period t+10* parallel to the axis marked *Period t* indicates convergence in emission per capita rates – starting at any rate in period *t* countries are likely to end up at the same (relative) rate in period *t+10*.

Consider Figures 8 and 9. Axis markings indicate relative emissions per capita – a 2 therefore, refers to 2 times the average emissions per capita rate. The stochastic kernel graphed in Figures 8 and 9 indicates significant persistence at low relative emission per capita rates. There is a clear ridge that extends close to the 45° line until emission levels of around 5 times the average per capita rate. At higher rates the ridge swings around indicating some convergence at higher relative rates of emissions per capita. There are, however, only a few observations available at these higher rates (see Figure 5) and caution is needed when interpreting this last result. (See Pagan and Ullah, 1999, pp58-60, for some discussion of the large sample requirements when estimating multivariate densities.)

Figures 10 and 11 indicate a slightly different story, at least at higher rates of emissions per capita. Axis markings in these figures indicate level deviations from the mean – a 2 therefore, refers to an emissions per capita rate 2 metric tons above the average emissions per capita rate. The main ridge extends all the way along the 45° line that indicates persistence. In relative levels terms, there is no evidence of convergence.

The general conclusion from this analysis is that there is little evidence of convergence in emission per capita rates.[3] Although in terms of proportional deviations from the mean there is some evidence of convergence at high relative rates of emissions per capita, this result does not hold when deviations from the mean in levels is considered. Any convergence at these higher rates is therefore very weak and dependent on the series transformation.

7. Conclusions

This paper presents the results of an empirical examination of fossil fuel CO_2 emissions per capita. A descriptive analysis of the key features of the distribution of emissions per capita is provided along with an analysis of the dynamics of this distribution over time. The distributional analysis is used to discuss the possibility of convergence in emissions per capita. Statistical examinations of the convergence hypothesis (that is, those based on summary measures) are often inadequate and uninformative and alternative transformations of the data can produce inconsistent results. The spread statistics considered in this paper suggest that emissions per capita across countries have diverged rather than converged.

The coefficient of variation suggests convergence and is inconsistent with the other statistical measures. This inconsistency highlights the difficulty in characterising data set properties with a single summary measure. The main conclusions in this paper are therefore based on a comprehensive examination of the distribution of emissions and the dynamics of this distribution over time.

Stochastic kernel based estimation techniques are used to estimate the distribution and intra-distributional dynamics of cross country emissions per capita over time. Although there is some weak evidence for convergence at very high rates of emissions per capita, overall there is little evidence for convergence in emissions per capita. The density of

[3] To check the robustness of these results to alternative time horizons the analysis is repeated for transitions over 20 years. The results (not presented here, but available on request) are consistent with the discussion presented here.

cross country emissions per capita appears to flatten over time consistent with the summary measures that suggest divergence rather than convergence.

The dynamic kernel estimates suggest that the cross country distribution of emissions per capita is characterised by persistence – countries with relatively low emission per capita rates are likely to remain in the lower part of the distribution and countries with relatively high emissions per capita are likely to remain in the upper part of the distribution.

Many climate models include assumptions that generate emission per capita projections that exhibit convergence. To be relevant, projection models should be based on some consideration of the empirical behaviour of key model variables. An empirical analysis of emissions per capita convergence is therefore an important factor in the assessment of projection models that generate convergent emission projections. Projections of future emissions should not be based on an assumption of convergence in emissions per capita because the empirical evidence suggests that there is little tendency towards convergence in emissions per capita.

The empirical evidence presented in this paper is also crucial to the debate over an appropriate emissions policy. Distributional features are an important consideration in the design of an appropriate policy response and in assessing the possible impacts of a policy proposal. A policy proposal that is based on convergence in emissions per capita will be more controversial if there is no tendency towards convergence in emissions per capita (as is suggested by the analysis in this paper) because the distributional impacts of the policy are likely to be significant.

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Table 1: Countries Included in our analysis

Afghanistan	Greece*	Nigeria
Albania	Grenada	Norway
Angola	Guatemala	North Korea
Argentina*	Guadeloupe	Papua New Guinea
Australia*	Guinea-Bissau	Paraguay
Austria*	Guyana	Peru*
Barbados	Haiti	Philippines
Belgium*	Honduras	Poland
Belize	Hong Kong	Portugal*
Bolivia	Hungary	Romania
Brazil	Iceland	Samoa
Bulgaria	India*	Sierra Leone
Cameroon	Ireland	Solomon Islands
Canada*	Israel	South Africa
Chile*	Italy*	South Korea
China*	Jamaica	Spain
Colombia	Japan*	Sri Lanka
Costa Rica	Jordan	Sudan
Cuba	Kenya	Suriname
Cyprus	Lebanon	Sweden*
Denmark*	Macau	Switzerland*
Dominica	Madagascar	Taiwan*
Dominican Republic	Malta	Thailand
Ecuador	Mauritius	Togo
Egypt	Mexico*	Trinidad and Tobago
El Salvador	Mongolia	Tunisia
Ethiopia	Morocco	Turkey*
Fiji	Mozambique	Uganda
Finland*	Myanmar	United Kingdom*
France*	Nepal	United States*
Gambia	Netherlands*	Uruguay
Germany*	New Zealand*	
Ghana	Nicaragua	

* indicates that this country is also included in Sample B.

Figure 1: World Fossil Fuel CO_2 Emissions

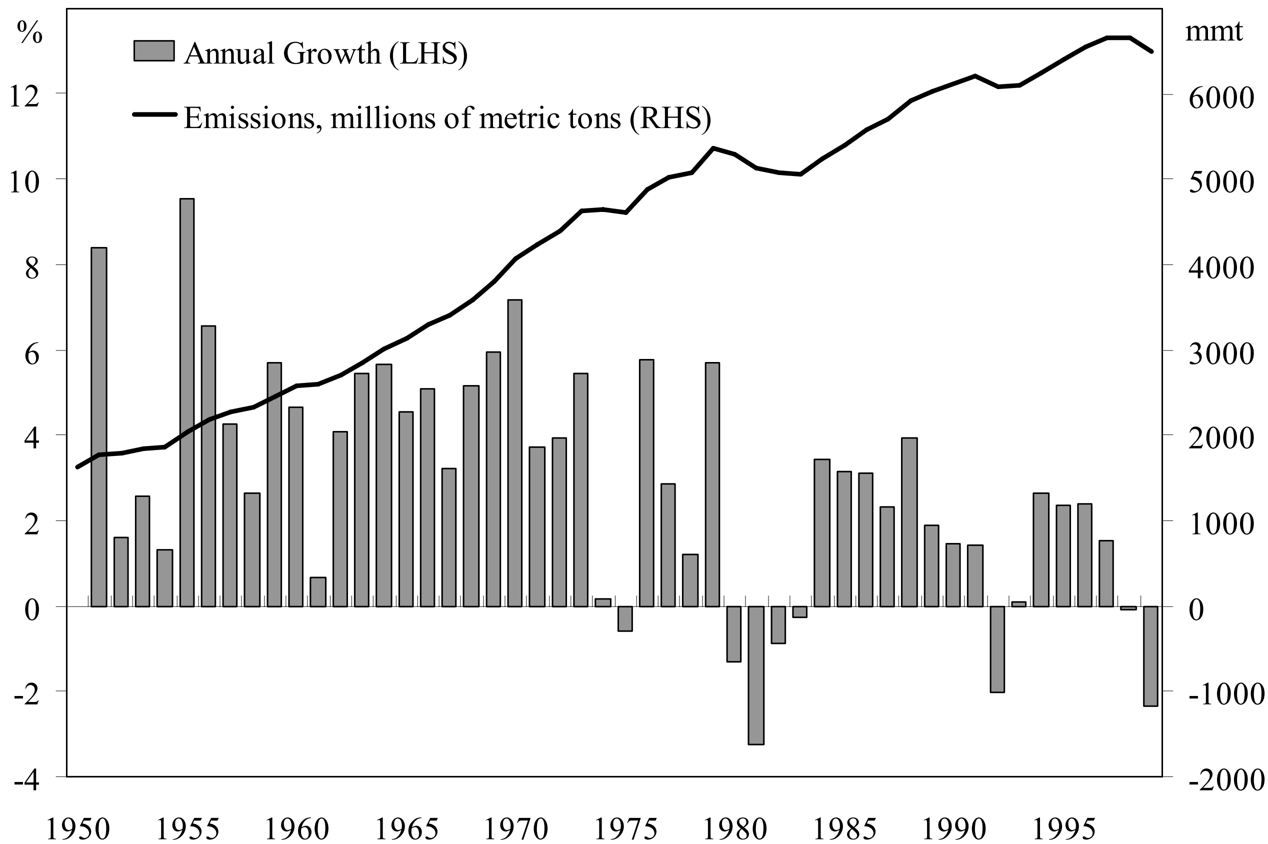

Figure 2: World Fossil Fuel CO_2 Emissions in 1950 and 1999

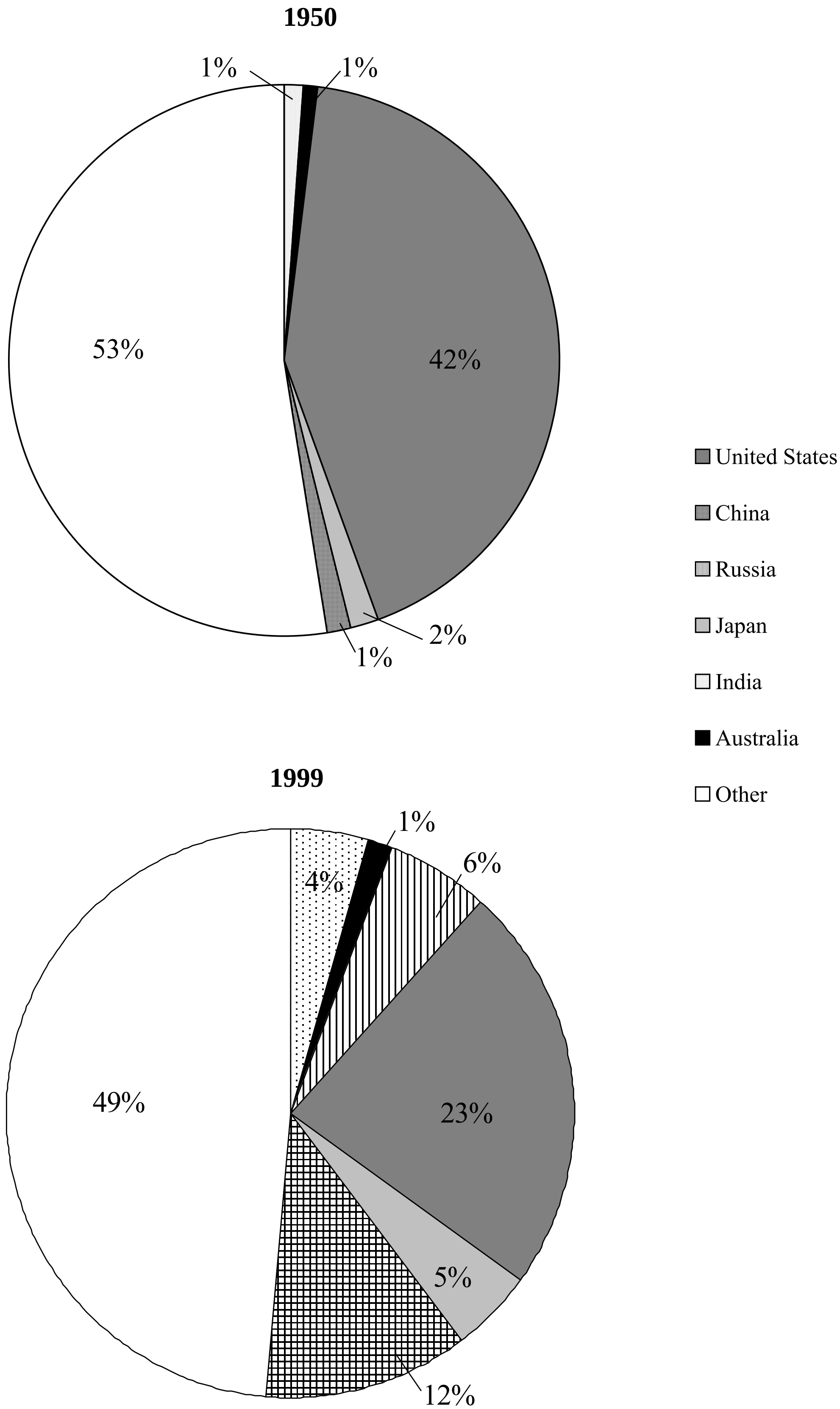

Figure 3: Summary Measures of Spread

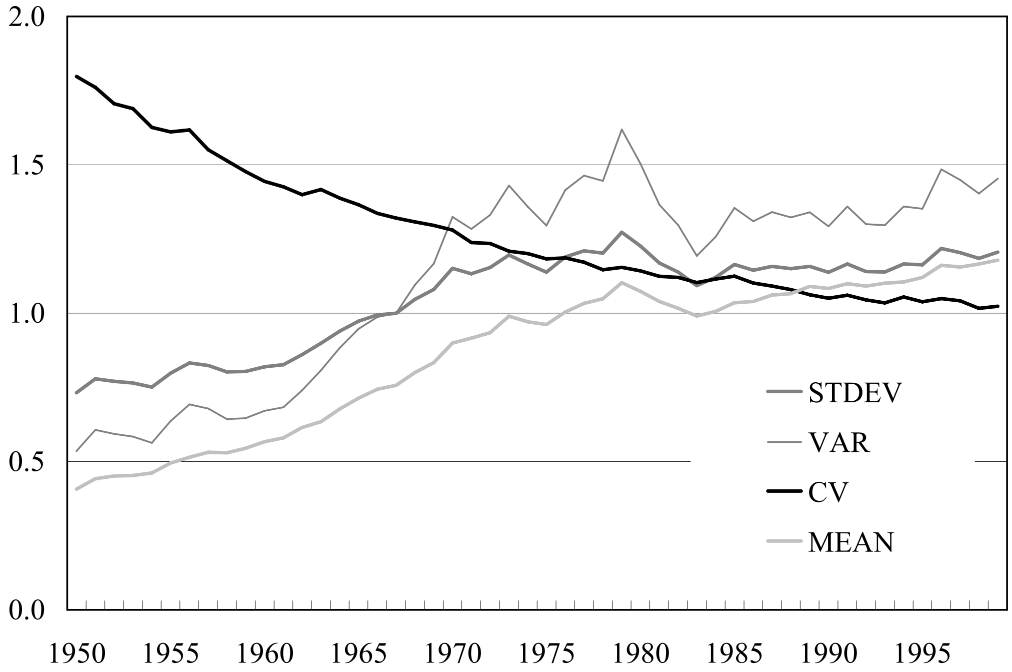

Figure 4: Summary Measures of Spread

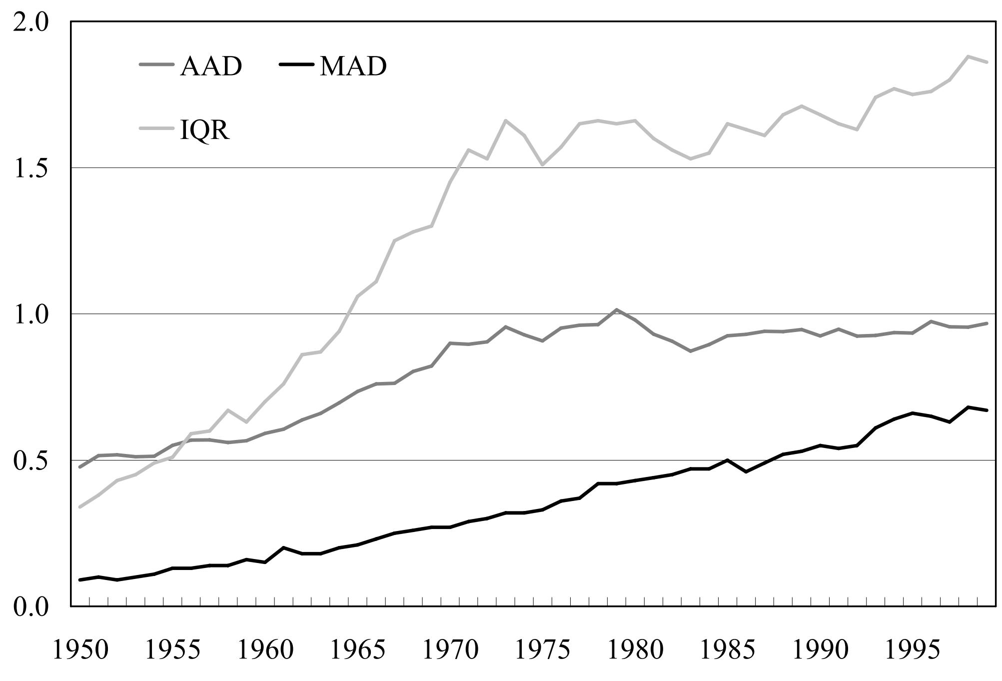

Figure 5: The Cross-Sectional Distribution of Emissions per Capita
Sample A

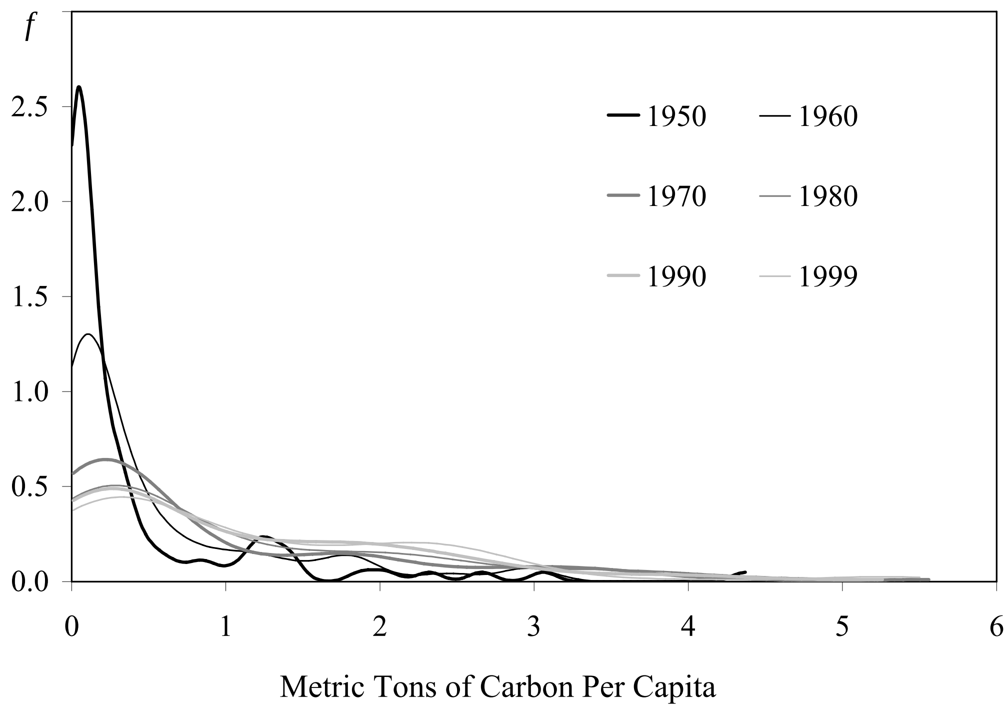

Figure 6: The Cross-Sectional Distribution of Emissions per Capita
Sample B

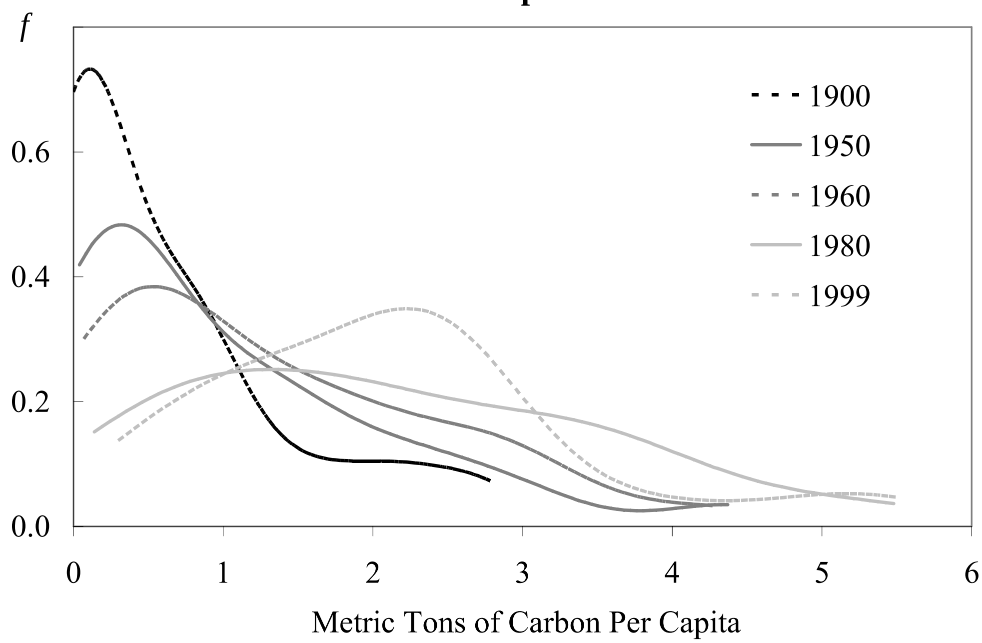

Figure 7: The Cross-Sectional Distribution of Relative Emissions per Capita
Sample A

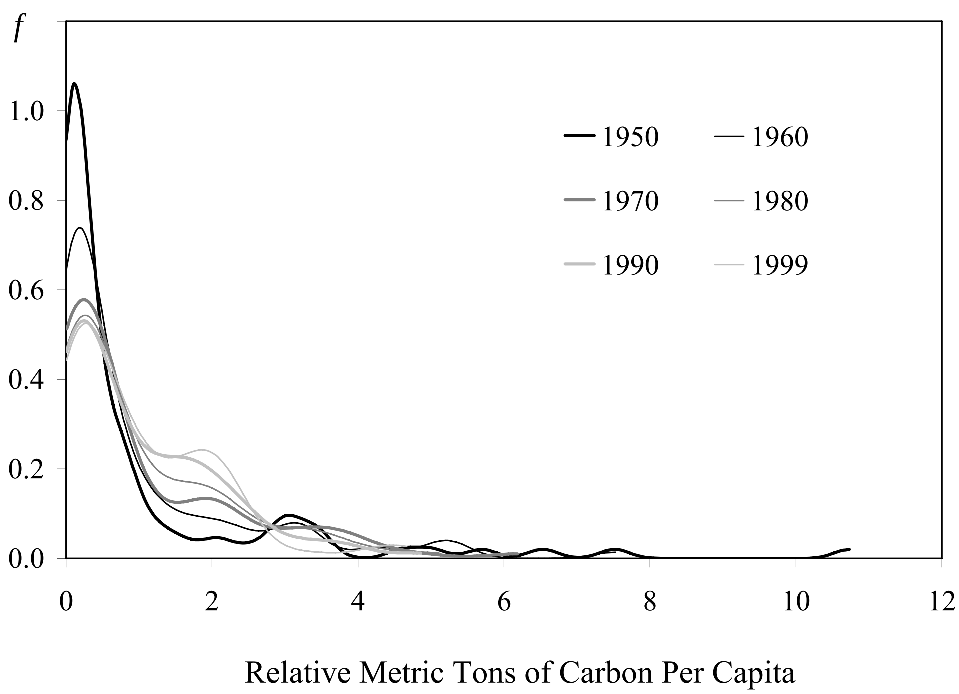

Figure 8: Relative Emissions per Capita Dynamics

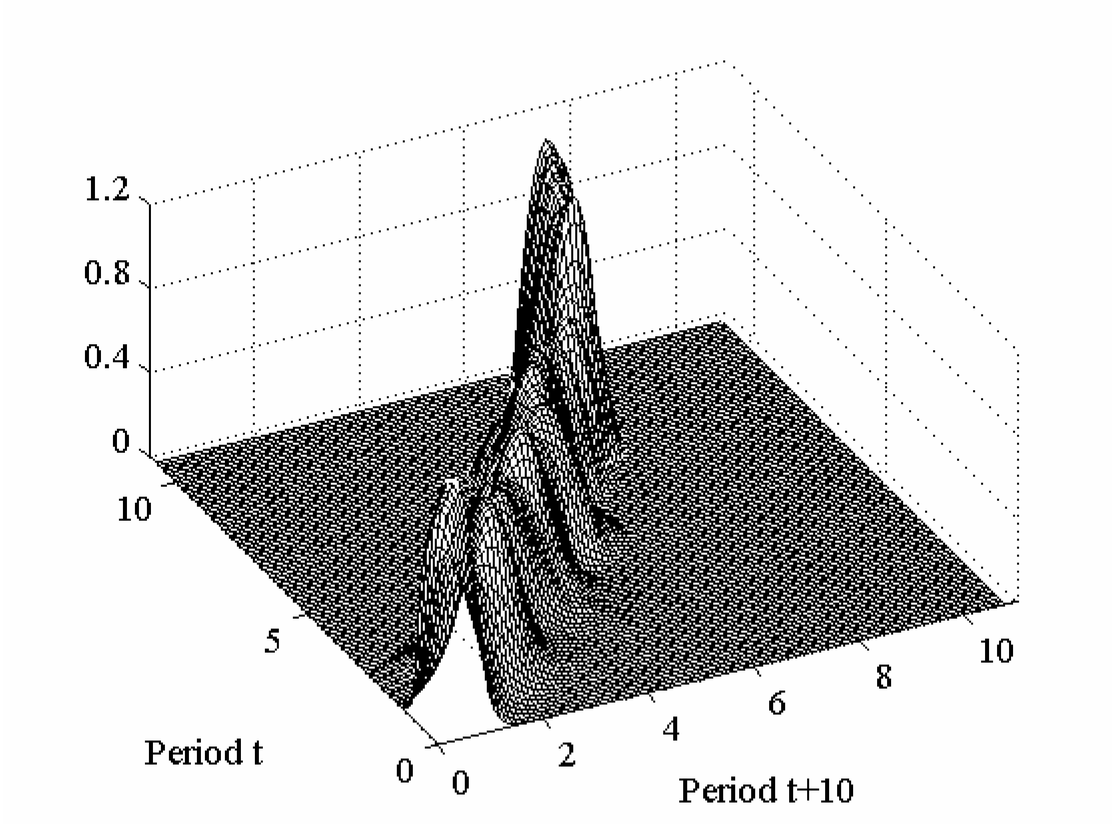

Figure 9: Relative Emissions per Capita Dynamics
Contour Plot

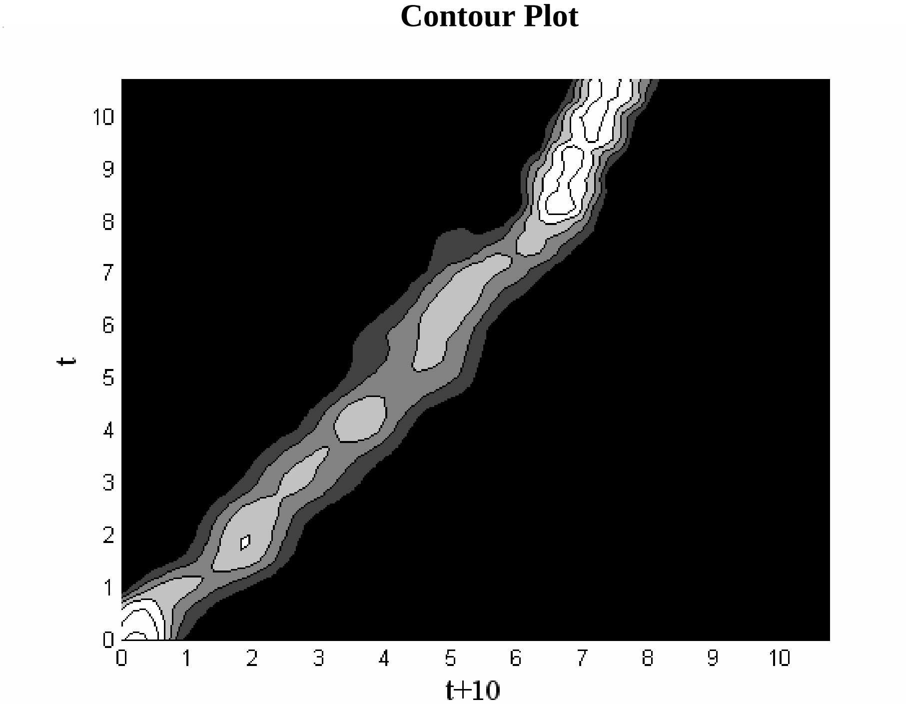

Figure 10: Levels Relative Emissions per Capita Dynamics

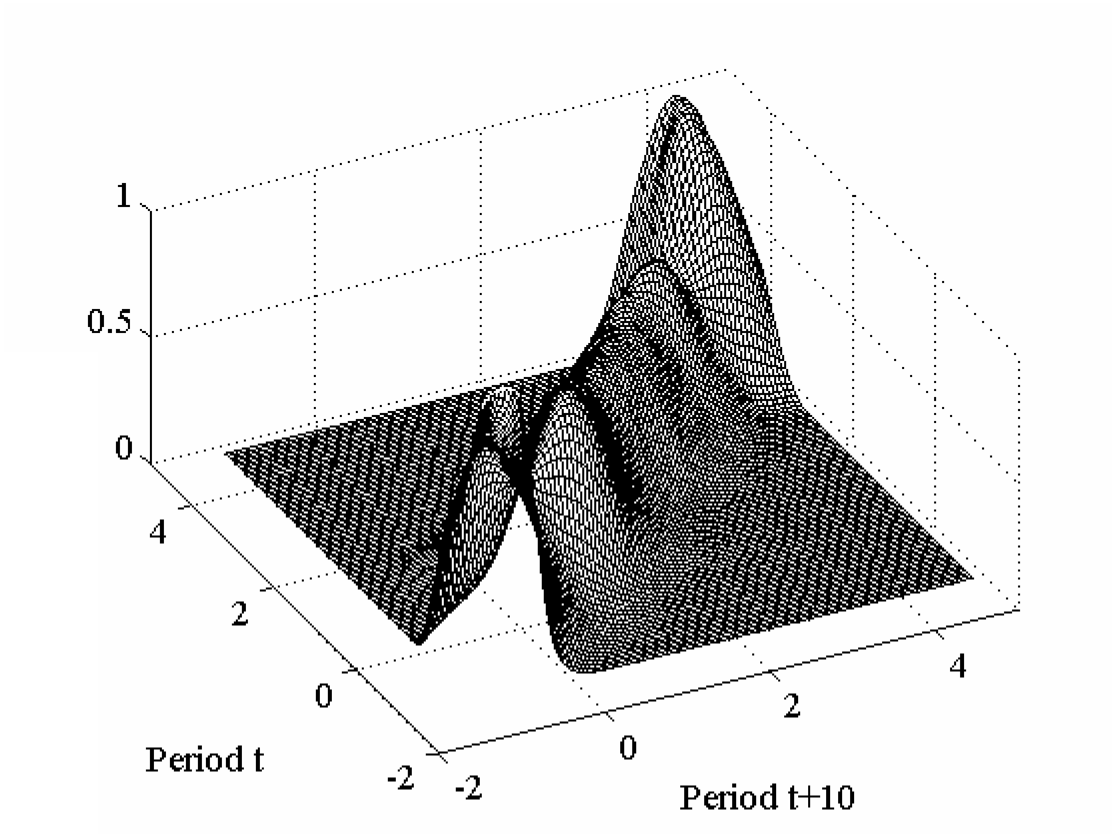

Figure 11: Levels Relative Emissions per Capita Dynamics Contour Plot