BROOKINGS DISCUSSION PAPERS IN INTERNATIONAL ECONOMICS

No. 167

CONVERGENCE AND PER CAPITA CARBON EMISSION

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MAY 2005

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Convergence and Per Capita Carbon Emissions*

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* This paper has benefited from discussions with Peter Wilcoxen and David Pearce and comments from Peter Downes and Neil Ferry. We are grateful to the Australian Greenhouse Office and Lowy Institute for financial support. The views expressed in the paper are those of the authors and should not be interpreted as reflecting the views of the Australian Greenhouse Office or the Institutions with which the authors are affiliated including the trustees, officers or other staff of the Lowy Institute or the Brookings Institution.
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Convergence and Per Capita Carbon Emissions

ABSTRACT

The notion of "convergence" of economic variables across countries is a useful concept and in the case of income per capita, a well studied area. If there is empirical evidence of convergence of some economic variables across countries, then our ability to predict the future (or at least differences between countries in the future) is enhanced. It is common in long run projections of climate change to base these projections on some notion of full or partial convergence whether in incomes per capita, technologies, energy intensities, emissions intensities of energy or per capita carbon emissions. But what is the empirical basis of these assumptions? This paper explores the historical experience of a range of variables related to climate change projections with the goal of examining if there is any evidence historically of convergence. The focus of the paper is on per capita carbon emissions from fossil fuel use because this is the basis of many projections as well as a variety of policy proposals. We also present evidence on GDP per capita, energy intensity of output and the emissions intensity of energy supply. We find strong evidence that the wide variety of assumptions about "convergence" commonly used in emissions projections are not based on empirically observed phenomena.

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Keywords:
Climate change, G-Cubed, model, projections, SRES, convergence, carbon emissions

JEL classification: C50, C68, F01, F43, Q54, Q56

1. Introduction

A key aspect of future projections of climate change is projections of future emissions of carbon dioxide. As shown by McKibbin, Pearce and Stegman (2004) the projection of greenhouse emissions depends importantly on future projections of economic growth, and the sources of that growth both within sectors and across countries. A central notion in the policy debate and in some projection approaches is assumptions about per capita carbon emissions. Some projection methodologies assume convergence of per capita emissions[1]. Yet given that fossil fuels are endowed on countries and relatively expensive to transport, it is difficult to see any conceptual reason why carbon dioxide emissions from fossil fuels should converge across countries on a per capita basis. This is an empirical question, yet in the climate change literature, assumptions rather than empirical evidence tends to drive much of the debate.

The Intergovernmental Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (SRES, IPCC, 2000) is one of the most comprehensive and well-known studies of future emissions projections. Since its publication, the report has received considerable critical attention, particularly in relation to the treatment of uncertainty within the report (Schneider, 2001) and to the assumptions regarding economic growth and convergence in some of the scenarios (see Castles and Henderson, 2003a and 2003b). There are wider issues regarding the methodology in this report apart from the existing debate. A critical issue is the basis of the projection methodology underlying many of the models used.

This paper examines the appropriateness of convergence assumptions used in long term emission projection models. The notion of convergence in one form or another over a range of

[1] Some policy proposals such as the "contraction and convergence" literature argue for policies that force convergence over time (e.g. see Bohringer, C and Welsch, H (1999), Meyer, A (2000), Pearce, F (2003), and WBGU Special Report (2003)).

variables often underlies model projections of the world economy. Most frequently, these assumptions about convergence relate to income per capita or productivity convergence. The SRES (IPCC, 2000) includes long run projections of emissions that are based on assumptions of convergence, not only in income per capita but also in the energy intensity of output. These assumptions have implications for the distribution of emissions per capita. This report explores the convergence properties of a number of economic variables that relate directly to energy use and fossil fuel emissions. Understanding the cross country distribution of these variables and the dynamic behaviour of these distributions is a crucial step in evaluating the appropriateness of including convergence assumptions in long run projection models.

The distribution of emissions per capita across countries and factors that affect the distribution over time can be further examined by considering the distributions of GDP per capita, the energy intensity of output and the emissions intensity of energy supplied.

A useful starting point is the following equation known as the IPAT identity (Ehrlich and Holdren, 1972):

$$\text{Impact} = \text{Population} \times \text{Affluence} \times \text{Technology}$$

which can be expressed as

$$\text{Emissions} = \text{Population} \times \text{GDP per capita} \times \text{Emissions per GDP} \qquad (1)$$

$$E \quad = \quad P \quad \times \quad GDPPC \quad \times \quad I \;\; \text{(Emissions Intensity)}$$

If population growth (p), GDP per capita growth ($gdppc$) and growth in emissions intensity (i) are independent then the IPAT identity can be approximated by a linear expression in growth rates:

$$e = p + gdppc + i \qquad (2)$$

and changes in income per capita growth, changes in the emissions intensity of output or changes in population would result in corresponding changes in emissions growth.

With endogenous right hand side variables, however, the relationship between right hand side changes and emissions growth becomes unclear.

The analysis in this report focuses primarily on emissions *per capita* but we also explore other elements of the identity such as energy intensity. The IPAT identity can be rewritten in terms of emissions per capita and technology can be expressed using energy variables:

Emissions/Capita =

$$\text{GDP /Capita} \times \text{Energy Supplied}^{2}\text{/GDP} \times \text{Emissions/Energy Supplied} \qquad (3)$$

This equation provides a foundation for the analysis of emissions per capita and the distribution of emissions per capita across countries and through time. Convergence in emissions per capita across countries could occur without convergence in the right hand side variables of Equation 3. Likewise, one or two of the right hand side variables could converge, but one variable could diverge to the extent that emissions per capita fail to converge.

The study begins with a detailed examination of the distribution of emissions per capita. A number of statistical methods are employed to examine the issue of convergence in emissions per capita. The statistical analysis examines *unconditional* convergence. *Conditional* convergence refers to convergence that exists as long as certain characteristics across the sample

[2] Total primary energy supplied (TPES) is calculated as the production of primary energy plus imports, minus exports, minus international marine bunkers, plus or minus stock changes. Production is the production of primary energy: hard coal, lignite/brown coal, peat, crude oil, natural gas liquids, natural gas, combustible renewables and wastes, nuclear, hydro, geothermal, solar and the heat from heat pumps that is extracted from the ambient environment. Total primary energy supply for a country differs from total final consumption (TFC) in that TFC measures consumption by end-use sectors. TPES includes energy consumed in the energy sector. The results in this section are not sensitive to the measurement of energy usage as either TFC or TPES. (IEA, 2004a)

remain the same. Unconditional convergence does not require this restriction. Overall we find little evidence for convergence in emissions per capita when analysed appropriately. Section 2 considers convergence in several other key energy and emission variables: **GDP per capita**, the **energy intensity** of output and the **emissions intensity** of energy supplied. There is little evidence of cross country convergence in these variables. In Section 3, factors that are likely to lead to differences in key energy and emissions variables are considered. The factors examined include differences in **fossil fuel endowments**, differences in the **composition of energy supplied** and the overall **composition of economic activity**, and **differences in the costs and prices** associated with energy use. Section 4 examines the existence of beta convergence (a negative relationship between the growth rate of emissions per capita over a period and the initial level) and its relationship to the distributional analysis in Section 2. The final section considers the implications of these findings for long run projections of future emissions. It is extremely worrying that many projections are based on various notions of convergence when this has not been observed historically. More importantly our results suggest that policies that aim to impose convergence of per capita emissions are likely to be high cost especially if as we argue, endowments of fossil fuels largely determine emissions of carbon from burning these fuels. Why would it be sensible to incur additional costs to have all citizens of the world produce the same emissions per capita when endowments of carbon differ across countries?

2. The Cross Country Distribution of Fossil Fuel Emissions Per Capita

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. Rather, 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 the data set. This definition is often referred to as 'σ-convergence' in the growth literature. With data that is not normally distributed, however, this definition may 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.

The main data set in this section is denoted Sample A. It includes 97 countries over the period 1950 to 1999. 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. Further details of these samples are contained in the Appendix.

2.1. Summary Measures

This section examines a variety of summary statistics used to measure the spread or variability of a data set (NIST/SEMATECH, 2003). Six measures are considered: 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 Appendix provides details on the calculation of each of these measures. All of the 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.

In Figures 1 and 2, contain estimates of each of the measures for Sample A over the period 1950 to 1999. Emissions per capita are measured as metric tons of carbon per capita.

Figure 1: Summary Measures of Spread
Emissions Per Capita

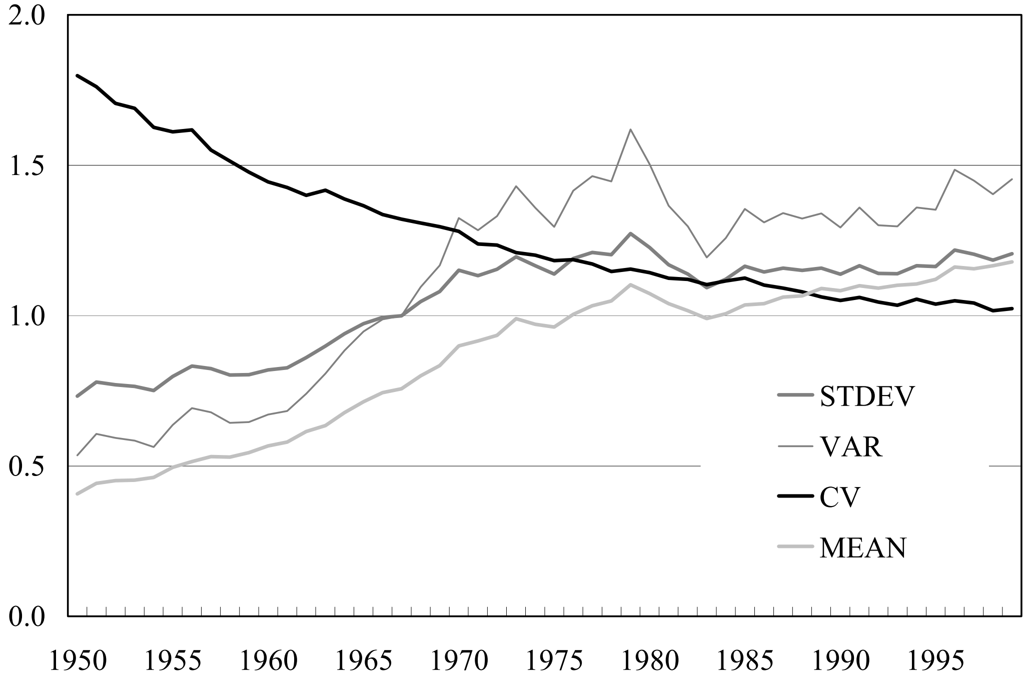
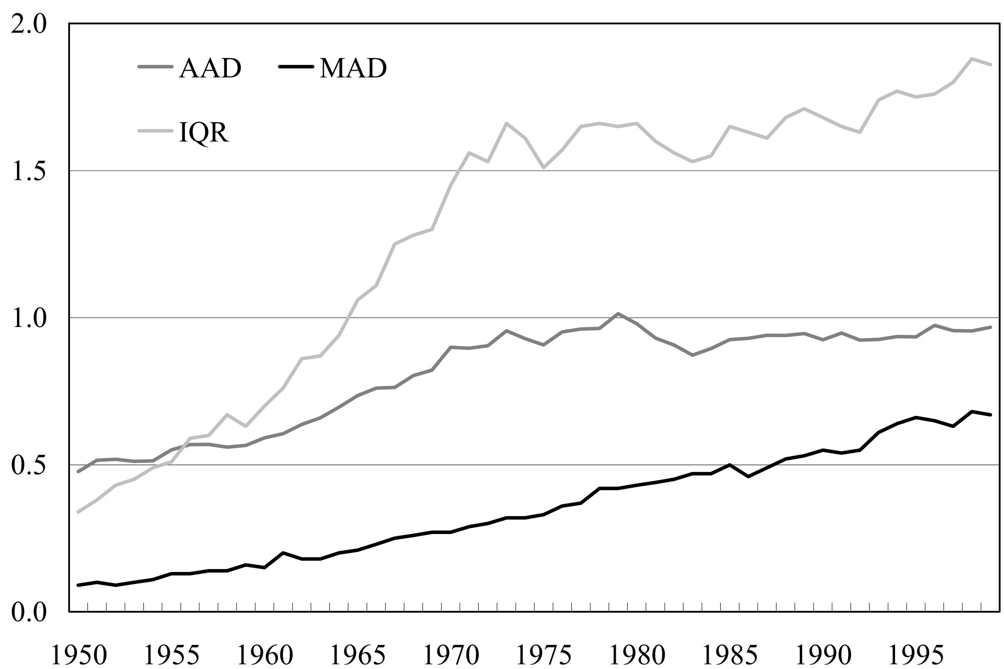


Figure 2: Summary Measures of Spread
Emissions Per Capita



In Figure 1, the mean, 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 increased by more than the standard deviation (which increases only slightly) and, as a result, the coefficient of variation falls over the period. Both the average absolute deviation and the median absolute deviation of Sample A increase over the period 1950 to 1999. The IQR, which only looks at the spread in the centre of the distribution, is also increasing over the time period (Figure 2).

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. This interpretation is not consistent with a series that exhibits unconditional convergence.

2.2. Distributional Analysis

This section examines the cross-country distribution of fossil fuel CO_2 emissions. General information on the distributional dynamics of fossil fuel CO_2 emissions per capita is presented. The particular question of convergence in emissions per capita rates is considered. 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 degenerate point limit (Quah, 1997). Progress in this area would then depend upon the series under consideration. For example, the statistical analysis of the previous section 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 considered so that the definition of convergence depends on the *percentage* deviation between countries. Analyses that seek to study convergence must clearly define the definition of convergence used and how it relates to the series under consideration. The study presented here analyses 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 (1995, 1997) to study income convergence. Kernel-smoothed estimates of the cross-country density of fossil fuel CO_2 emissions over time are plotted. Plotting the cross-country density over time provides information on how the *shape* of the distribution is evolving. Details of the estimation techniques are contained in the Appendix. Readers unfamiliar with non parametric density estimation may prefer to consider the density graphs as continuous histograms where the area under the curves has been normalised to unity. The vertical axis, denoted *f,* is therefore a normalised measure of frequency. The intra-distributional dynamics of this distribution over time are then examined. The stochastic kernel detailed in Quah (1995) is used to estimate these dynamics. The calculation of the stochastic kernel estimates is similar to the calculation of a non parametric conditional density function.

In Figures 3, 4 and 5 kernel-smoothed cross-country densities for fossil fuel CO_2 emissions per capita are presented. In Figure 3, 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. In Figure 4, the smaller sample of countries (Sample B) for which data is available from 1900 onwards is examined.

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 be expected to have increased over this time period (this is confirmed by the summary statistics of the previous section). 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 4, 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 5, plots the density estimates for relative emissions per capita rates based on Sample A. The data under consideration is the emissions per capita rate 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 3. The interesting differences are less flattening in the distribution over time and a substantial change in the range of the distribution over time. This result may help explain why the coefficient of variation for the original data set (graphed in the previous section), which is the standard deviation for this relative data set, decreases over time.

Figure 3: The Cross-Sectional Distribution of Emissions per Capita Sample A

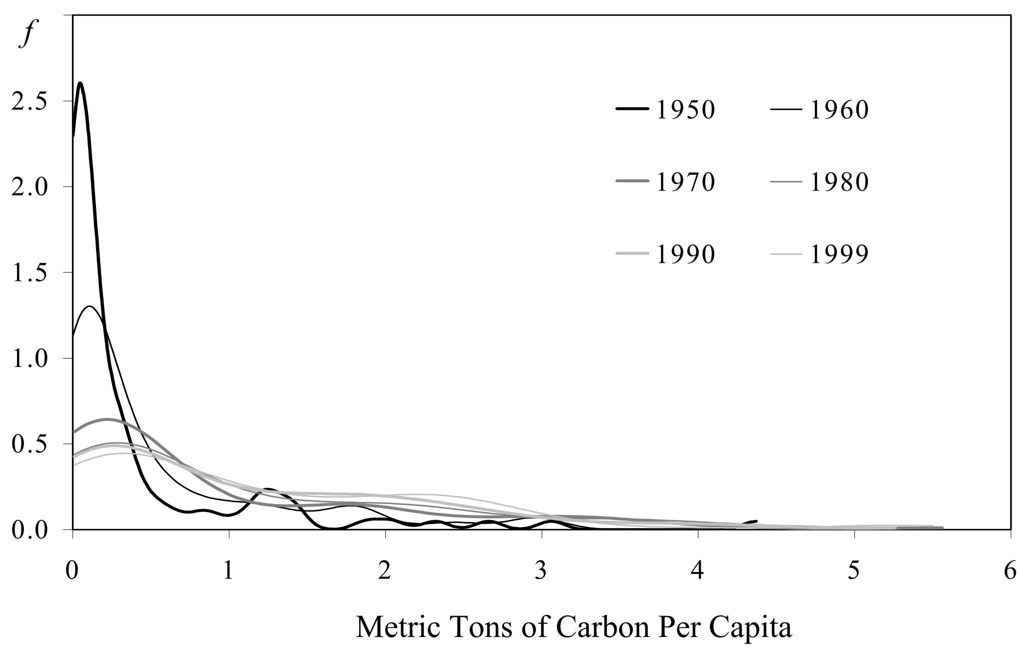


Figure 4: The Cross-Sectional Distribution of Emissions per Capita
Sample B

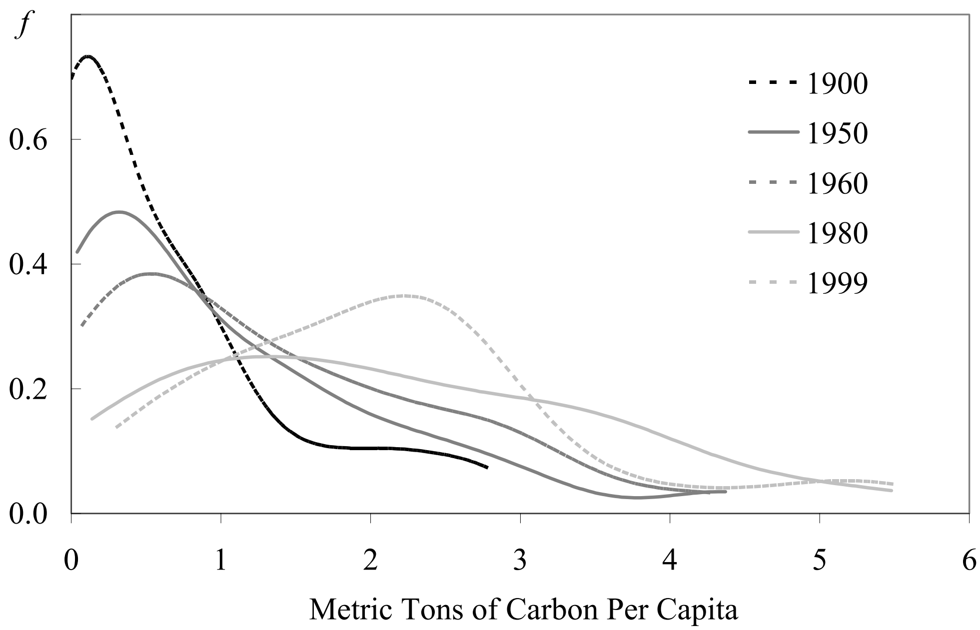
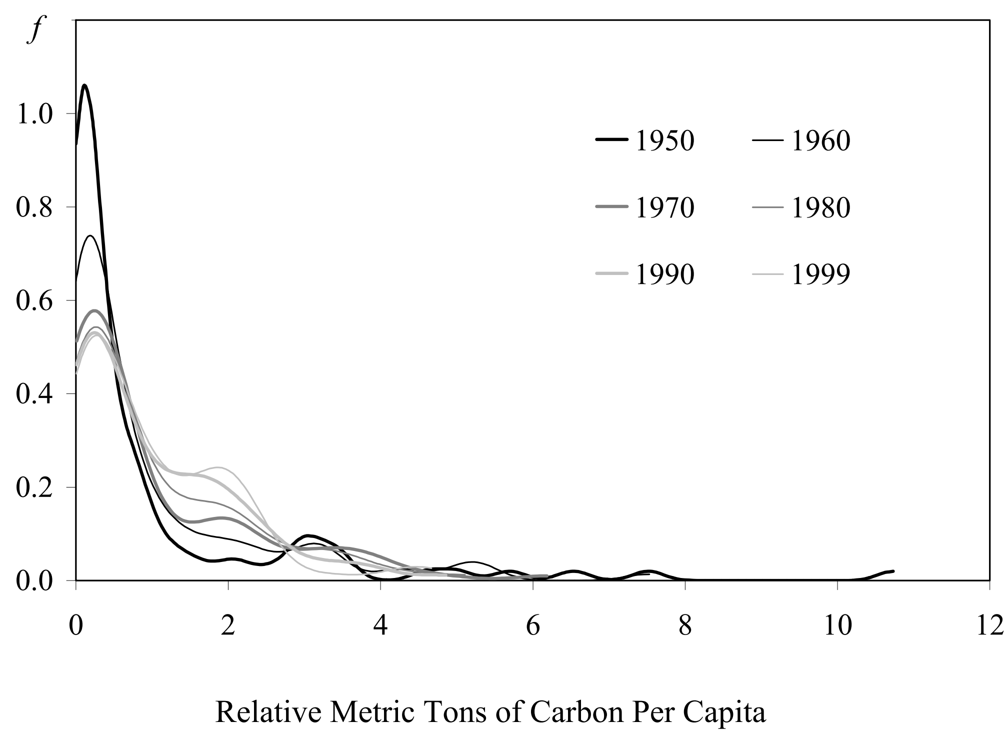


Figure 5: The Cross-Sectional Distribution of Relative Emissions per Capita
Sample A



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 3 and 5, such a transformation may affect the conclusions drawn. In analysing the dynamics of emissions per capita, the concept of convergence in both levels and in proportions to the mean is considered. Two data transformations are used in what follows. Firstly, a *relative emissions per capita* series, defined as above. This series measures proportional deviations from the cross-country mean. Secondly, from the original (levels) series, the cross-country mean at time t from each observation at time t is subtracted. This series, denoted *levels relative emissions per capita*, measures level deviations from the mean. In Figures 6 and 8 the stochastic kernels for each of these series is plotted and Figures 7 and 9 contain the corresponding contour graphs. In both cases, the time period over which transitions is measured is 10 years.

Interpreting these graphs is relatively simple. As discussed above, their interpretation is similar to a conditional density function. 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 6 and 7. Axis markings indicate relative emissions per capita – a 2 therefore, refers to 2 times the cross country average emissions per capita rate. The stochastic kernel graphed in Figures 6 and 7 indicates significant persistence at low relative emissions 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 8 and 9 indicate a slightly different story. 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. 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 above.

The general conclusion from this analysis is that there is little evidence of convergence in emissions per capita rates. 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.

Figure 6: Relative Emissions per Capita Dynamics

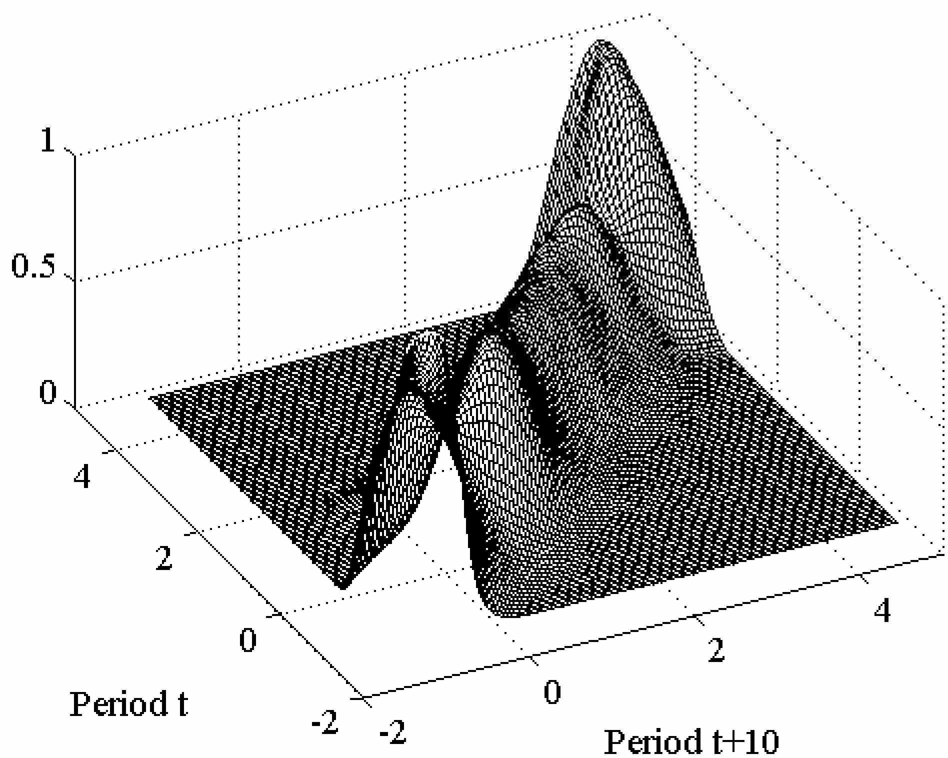


Figure 7: Relative Emissions per Capita Dynamics
Contour Plot

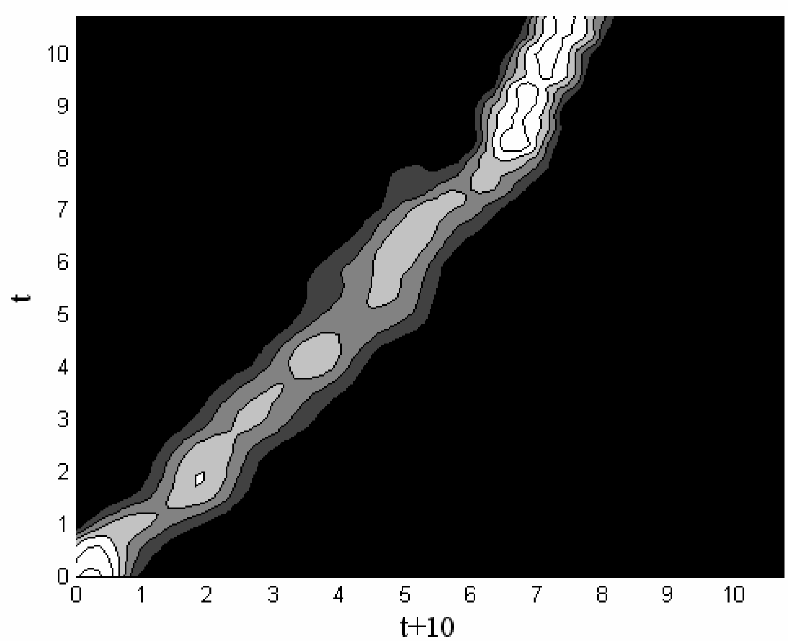


Figure 8: Levels Relative Emissions per Capita Dynamics

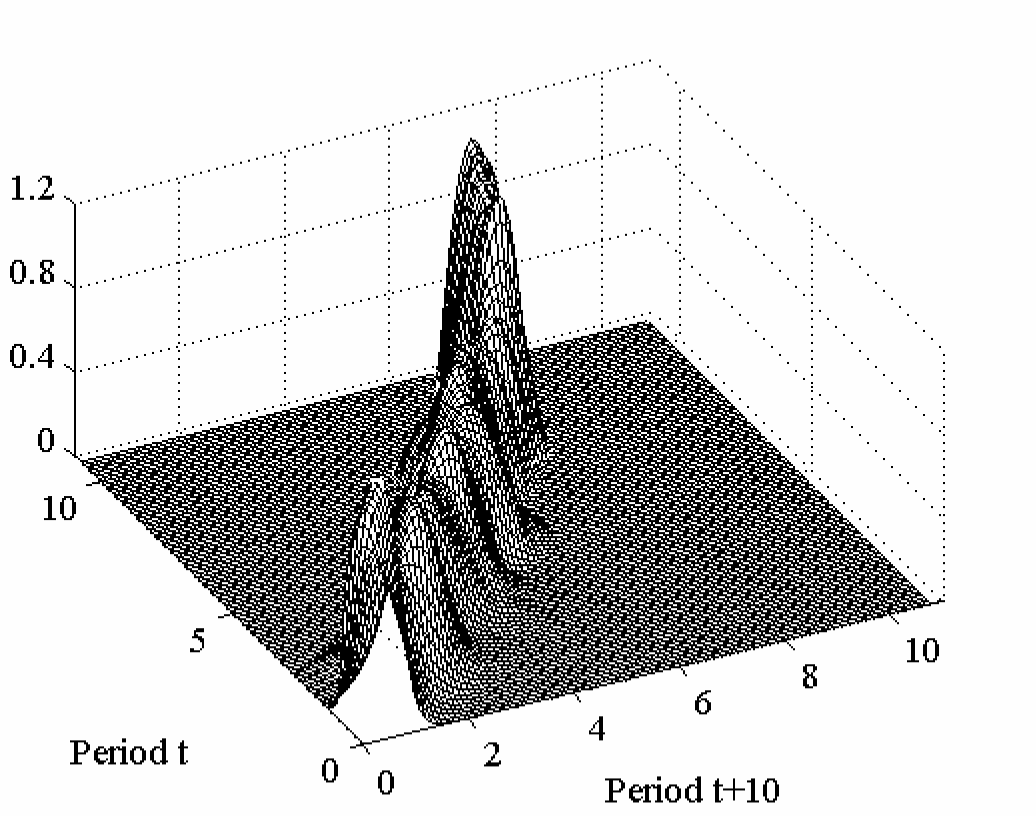
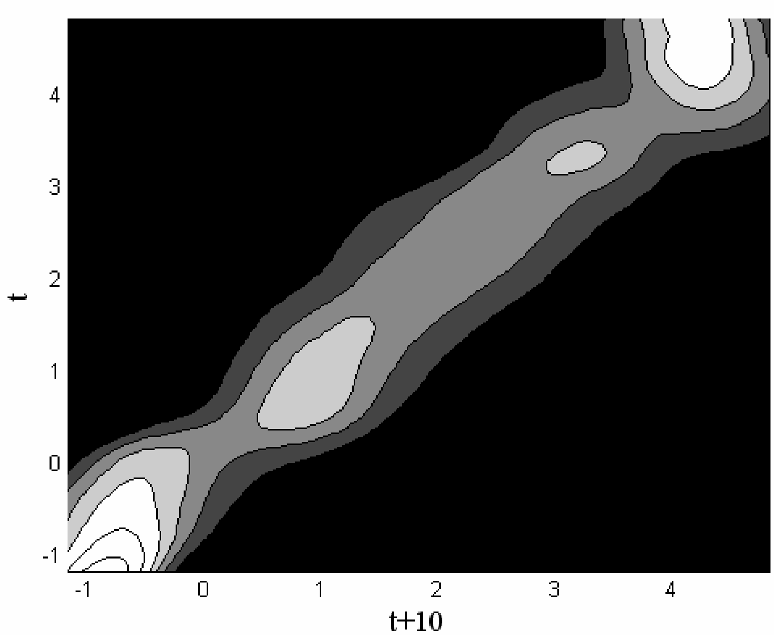


Figure 9: Levels Relative Emissions per Capita Dynamics Contour Plot



3. *The Distribution of GDP Per Capita, the Energy Intensity of Output and the Emissions Intensity of Energy Supplied*

This section explores the right hand side of the IPAT identity to see what components of GDP per capita, energy intensity of output or the emissions intensity of energy supplied, are responsible for the non-convergence of emissions per capita.

The data in this section is sourced from the International Energy Agency (IEA, 2004a, 2004b). The GDP variables are all measured using 1995 purchasing power parities (PPPs) and denoted in US$. The data sets are measured relative to (as a proportion of) the cross-sectional mean. This allows changes in the shape of a distribution to be examined independently of general increases (or decreases) in the cross country mean of the series over time, as described in the previous section.

A shortcoming of the analysis is the limited availability of data prior to 1971. Non-OECD data is not available prior to this data. The distributional analysis of the previous section suggested that the shape of the cross country distribution of emissions per capita experienced the most change between 1950 and 1970. An analysis of the OECD region is therefore included, where possible, from 1960. Analysing a sub set of countries is equivalent to considering a conditional convergence hypothesis.

Further details of the data are contained in the Appendix.

3.1. <u>GDP Per Capita</u>

The neoclassical growth models of Ramsey (1928) and Solow (1956) suggest that there is an inverse relationship between the growth rate of income or output per capita and the initial starting level (Sala-i-Martin, 1996a). Sala-i-Martin and Barro (1992) argue that *if countries are similar with respect to preferences and technology* then poor countries tend to grow faster than rich countries and "there is a force that promotes convergence in levels of per capita product and income" (p224).

The model implies *conditional* convergence in that *for a given steady state*, the growth rate is higher the lower the initial level of output per effective labour unit. The neoclassical growth model does not predict *unconditional* convergence. Poor countries are predicted to grow faster than rich countries only if they share the same steady state characteristics.

Empirical research on convergence has received considerable attention in the economic literature. Most of this research is concerned with the distribution of income per capita (living standards) and, to a smaller extent, the distribution of output per worker or per hour worked (productivity).

Four broad approaches to convergence analysis can be identified in the literature: beta (β) convergence, sigma (σ) convergence, time series (co-integration) analysis, and distributional analysis. Sala-i-Martin (2002) and Quah (1995a) provide summaries of these alternative approaches to convergence analysis.

In general, there is little evidence for unconditional convergence of income per capita or productivity levels when a large cross section of countries is considered (see Sala-i- Martin (1996b) for β and σ convergence analyses, Quah (1995b) for a distributional analysis, and

Bernard and Durlauf (1995) for a time series analysis). The evidence for alternative forms of conditional convergence is stronger (see Quah (1995b, 1997) and Sala-i-Martin (1996a, 1996b)), although there is considerable debate about the appropriate interpretation of these results.

Figure 10 contains density estimates for relative GDP per capita levels from 1971 to 2000. GDP per capita levels are measured relative to (as a proportion of) the cross country mean so that a 2 on the *x*-axis represents two times the cross country average level of GDP per capita. The *y*-axis is a normalised frequency (*f*) as described in Section 2.

There is little evidence that GDP per capita levels are converging across countries. The density estimates reveal the "twin peak' (bimodal) behaviour characteristic of large sample GDP per capita distributions (see Quah, 1997).

Figure 11 contains density estimates for GDP per capita in the OECD region only. There is some evidence of convergence. The range of this relative distribution, which extends from around 0.25 of the OECD average to 2 times the OECD average, does not change much from 1960 to 2000. The shape of the distribution, however, becomes more peaked, suggesting that the majority of countries in the OECD are converging in terms of GDP per capita.

3.2. The Energy Intensity of Output

Figure 12 contains density estimates for the cross-country distribution of energy supplied per unit of GDP, where energy intensity is measured relative to (as a proportion of) the cross country mean of each series. There appears to be little change in the shape of the cross country distribution of the energy intensity of output.

Figure 10: The Cross Country Distribution of GDP Per Capita
Density Estimates

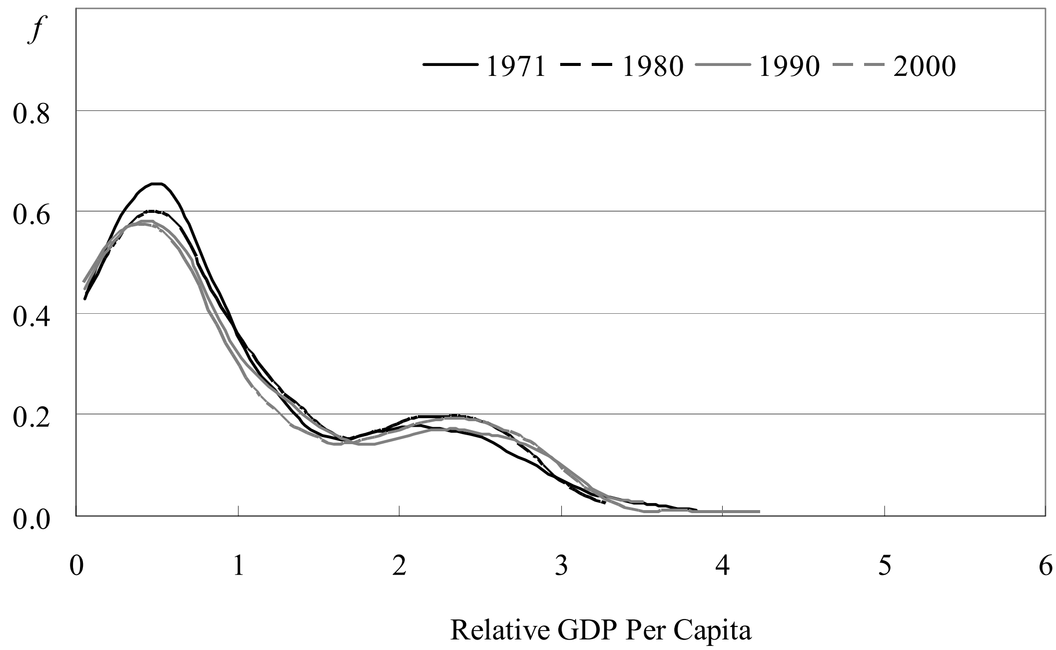


Figure 11: The Cross Country Distribution of GDP Per Capita
Density Estimates – OECD

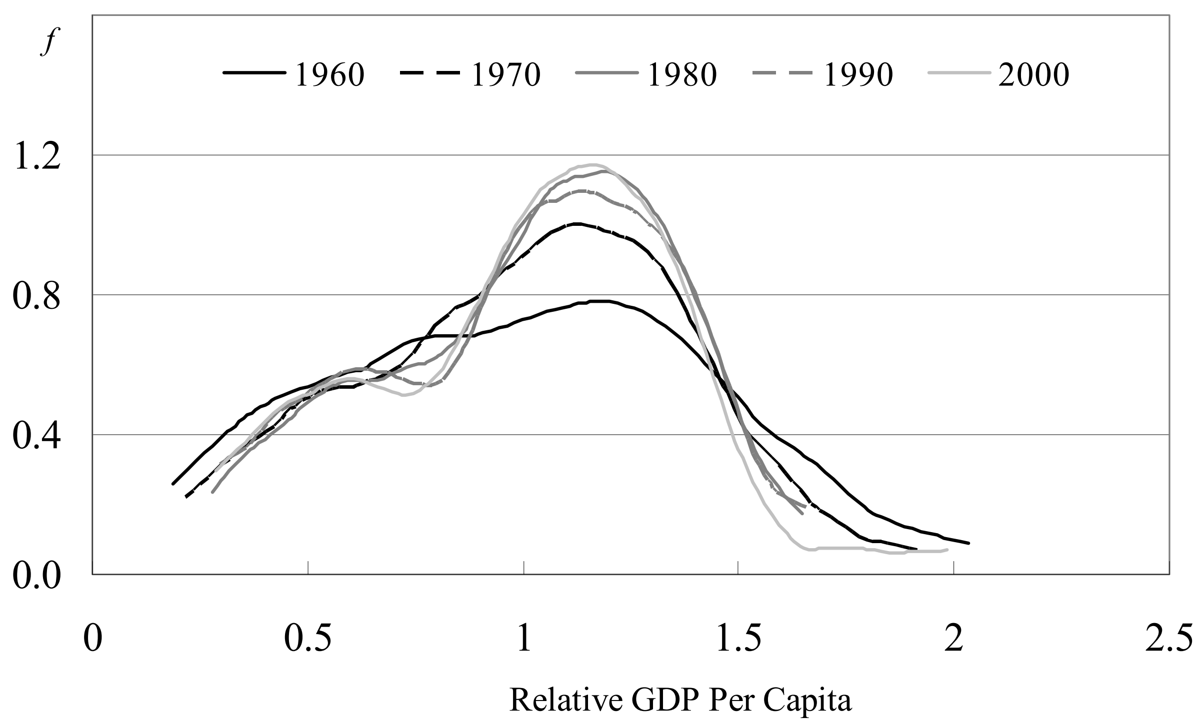


Figure 12: The Cross Country Distribution of Energy Supplied Per GDP Density Estimates

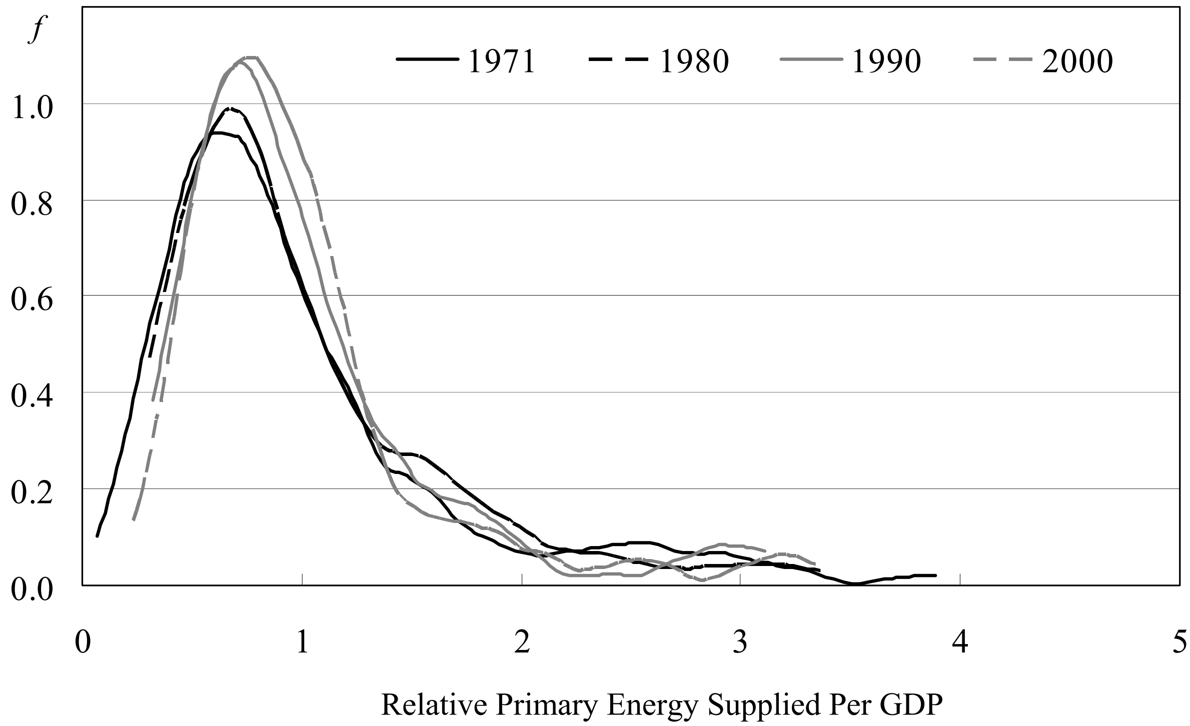


Figure 13: The Cross Country Distribution of Energy Supplied Per GDP Density Estimates – OECD

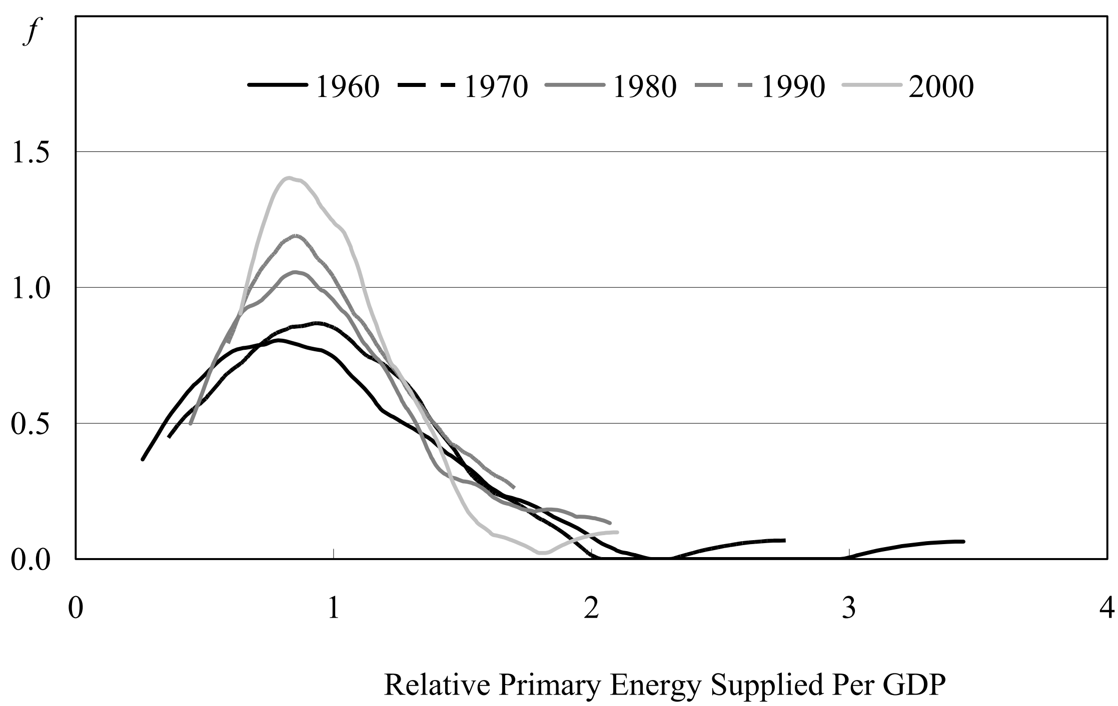


Figure 13 contains density estimates for the relative cross-country distribution of energy supplied per unit of GDP in the OECD region. In the OECD sample, there is some evidence of convergence in the energy intensity of output. The range of the distribution narrows and becomes more peaked around the OECD average.

3.3. The Emissions Intensity of Energy Supplied

Figure 14 contains density estimates for relative fossil fuel emissions per unit of energy supplied. From 1971 to 1990 the shape of the distribution of the emissions intensity of energy supplied shows little evidence of change. It exhibits a bimodal shape although very different to the GDP per capita distribution in Figure 10. The distribution in 2000, however, does not exhibit such a distinct bimodal shape although the distribution is still negatively skewed. There appears, therefore, to be some mobility in the distribution, but this is cannot be interpreted as evidence of convergence.

Figure 15 contains density estimates for relative fossil fuel emissions per unit of energy supplied for the OECD region. In contrast to the global sample, the OECD sample has more normal distribution. However there does not appear to be any evidence of convergence.

Figure 14: The Cross Country Distribution of Emissions Per Energy Supplied Density Estimates

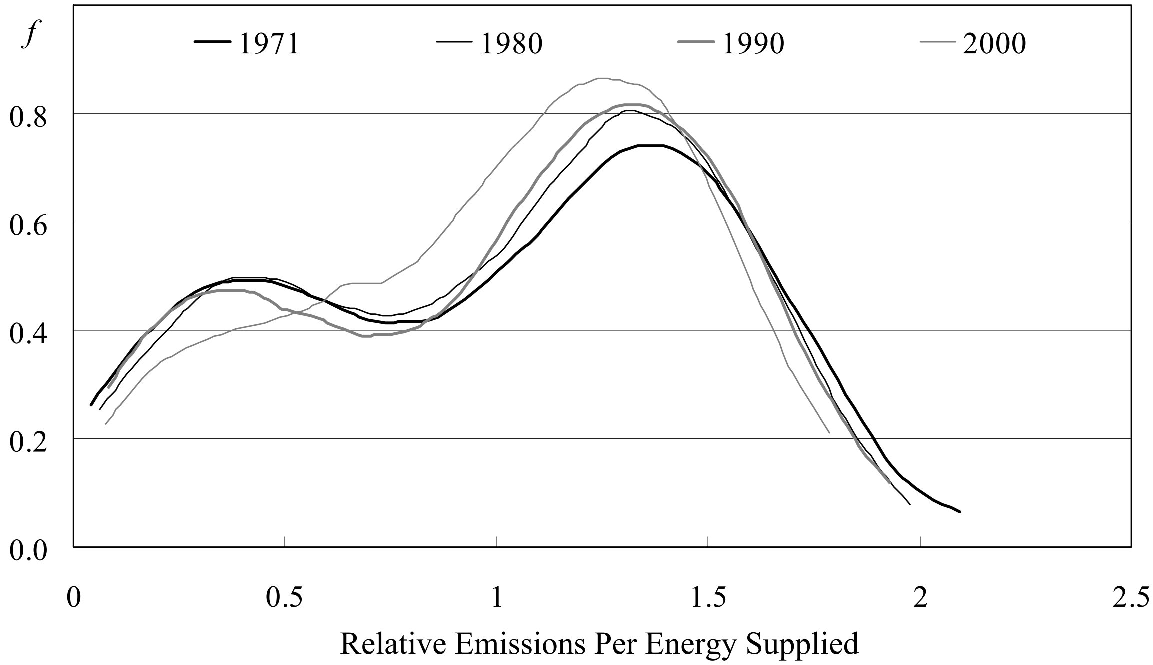
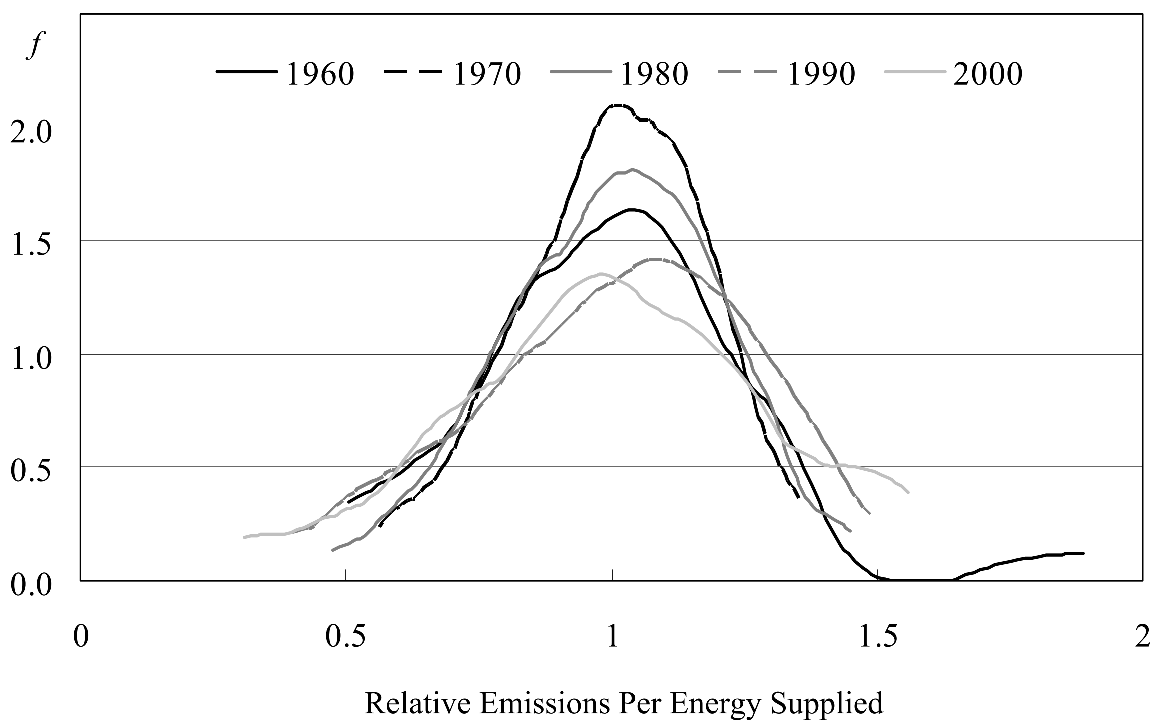


Figure 15: The Cross Country Distribution of Emissions Per Energy Supplied Density Estimates – OECD



3.4. Summary

This section examined the key components of emissions per capita, as outlined by the IPAT framework. Given the analysis in Section 2 that suggested there was little evidence of convergence in emission per capita rates, this section examined the evidence for convergence in three key variables: GDP per capita, the energy intensity of output and the emissions intensity of energy supplied, to assess whether trends in the cross country distribution of emissions per capita were a reflection of the general absence of convergence in key macroeconomic variables or if they were a reflection of divergence in a particular variable.

Because of data limitations the analysis was not as comprehensive as the detailed analysis of emissions per capita in Section 2, but the examination provides a good overview of the distribution of each variable over time.

Overall, there is little evidence of convergence in any of the variables when a large cross section of countries was considered. When the analysis is restricted to the OECD region, there is some evidence that the GDP per capita and energy supplied per unit of GDP variables were converging but there was no evidence that the emissions intensity of energy supplied was converging across OECD economies. If GDP per capita and energy supplied per unit of GDP converged, differences in emissions per capita may still persist because of differences in the fuel mix of energy supplied. The next section looks at factors that may help to explain differences in the energy intensity of output and the emissions intensity of energy supplied.

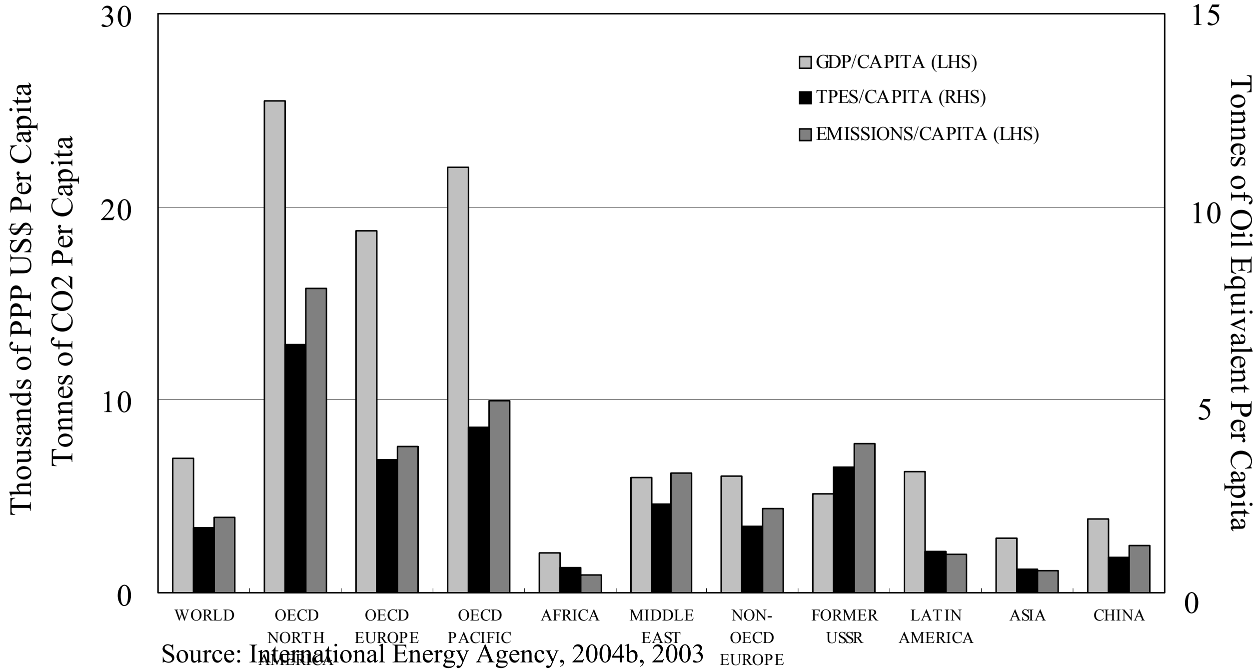
4. *Determinants of Key Energy and Emissions Variables Across Countries and Over Time*

The analysis in Section 2 suggested that there is little tendency for convergence in the levels of emissions per capita across countries. Section 3 disaggregated emissions per capita into three key variables: GDP per capita, energy supplied per unit of GDP and emissions per unit of energy supplied. There appeared to be little evidence of cross country convergence in any of these key variables when a large cross section of countries was considered. This section examines factors that are likely to determine the quantity and composition of energy supplied and fossil fuel emissions across countries and changes in the cross country distribution of emissions per capita over time. The factors considered include the **structure of economic activity**, differences in **fossil fuel endowments**, differences in the **structure of energy supplied**, and differences in the **costs and prices** associated with energy use. Each of these factors is considered in turn.

4.1. The Structure of Economic Activity

To provide an overview of the link between economic activity, energy supplied and fossil fuel emissions, Figure 16 plots per capita variables for GDP, energy supplied and emissions for major world regions in 2001. Figure 16 highlights the positive relationship between income, energy supplied and emissions. However, the relationship between these variables, when examined in the time dimension and in a more detailed cross section is more complex than suggested by Figure 16.

Figure 16: Key Variables in 2001

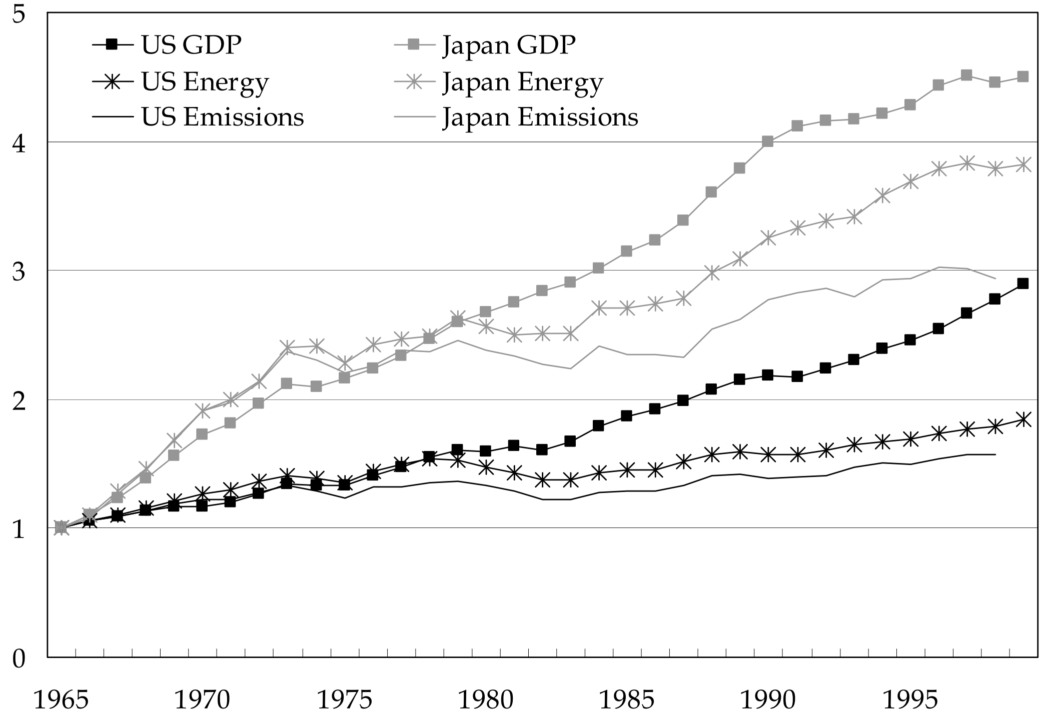


Source: International Energy Agency, 2004b, 2003

The relationship between emissions and GDP critically depends on the emissions intensity of GDP which in turn is determined by the energy intensity of GDP and the emissions intensity of energy supplied. The emissions intensity of output therefore depends on the relative prices of energy and non-energy inputs, and emitting and non-emitting energy sources as well as on the ability to substitute between these inputs (and their relative shares in production). Relative input and energy prices will change as a result of changes in the drivers of growth, which may be concentrated in particular sectors of the economy.

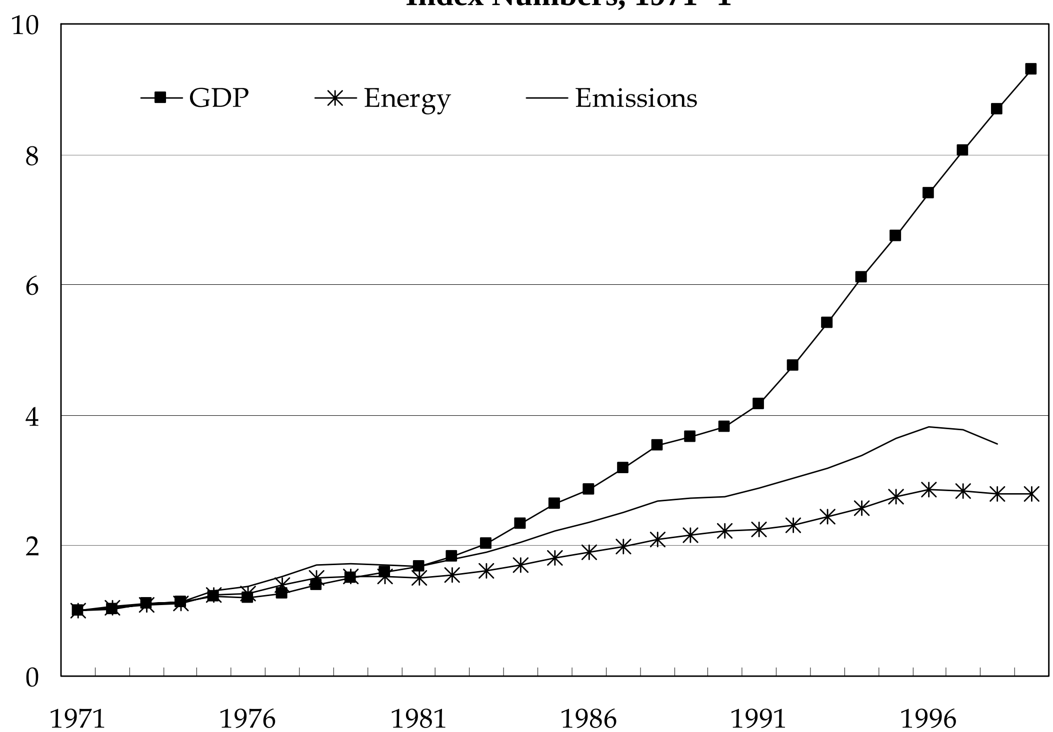
Figure 17 plots GDP, energy consumption and emissions for the United States and Japan as index numbers from 1965. Energy numbers for China are available from 1971 onwards and Figure 18 plots GDP, energy consumption and emissions for China as index numbers from 1971.

Figure 17: GDP, Energy and Emissions Index Numbers, 1965=1



Source: Energy Information Administration, 2004 and WDI 2002

Figure 18: China GDP, Energy and Emissions Index Numbers, 1971=1



Source: Energy Information Administration, 2004 and WDI 2002

Figures 17 and 18 demonstrate that there is no simple relationship between GDP and emissions. In the United States and Japan emissions and GDP appear to follow a common trend until 1972 when the OPEC oil price shocks dramatically changed the price of energy. In China there is no clear relationship between GDP and emissions. Emissions intensity (emissions per unit of GDP) increases until 1978/1979, when China began implementing extensive economic reform. This reform was accompanied by rapid economic expansion and GDP growth. At the same time, reforms in the energy sector helped to reduce energy intensity and emissions intensity.

Changes in the relationship between GDP, energy use and emissions, such as those depicted in Figures 17 and 18, can result from changes within sectors as well as from compositional changes in the relative size of sectors with different energy intensities. Technological change can also contribute to such outcomes.

Figures 19 and 20 illustrate this point by demonstrating the impact of a simple productivity shock in the G-Cubed dynamic stochastic general equilibrium model. The G-Cubed model, which includes detailed country coverage, sectoral disaggregation and rich links between countries through goods and asset markets, is outlined in McKibbin and Wilcoxen (1998). Tables 1 and 2 outline the country and sectoral coverage of the version used in this analysis (Version 58E).

Figures 19 and 20 demonstrate the pattern of GDP growth and carbon emissions when assumptions about productivity growth at the sectoral level are changed. Each pair of bars represents the change in real GDP and carbon emissions in the United States when productivity growth of 1% per year for 50 years occurs in that sector.

Table 1: G-Cubed Version E Regions

Unites States of America	USA
Japan	JPN
Australia	AUS
Europe	EUR
Rest of the OECD	ROECD
China	CHN
Eastern Europe and the former Soviet Union	EEB
Oil Exporting Developing Countries	OPC
Other Developing Countries	LDC

Table 2: G-Cubed Sectors

	Energy:	
1		Electric Utilities
2		Gas Utilities
3		Petroleum Refining
4		Coal Mining
5		Crude Oil and Gas Extraction
	Non Energy:	
6		Mining
7		Agriculture, Fishing and Hunting
8		Forestry/ Wood Products
9		Durable Manufacturing
10		Non-Durable Manufacturing
11		Transportation
12		Services
Y		Capital Good Producing Sector

Each of the figures (19 and 20) contains 13 groups of two bars. Along the horizontal axis each of the 13 groups corresponds to the sector in which the increase in productivity occurs.

The percentage deviation in both emissions and economy wide GDP as a result of the productivity growth in sector *i* is shown on the vertical axis. In Figure 19, the vertical axis shows the impact of productivity growth on United States emissions and GDP by 2020 (18 years). In the services sector (Sector 12), the impact of productivity growth on GDP is larger than the increase in emissions. In the energy sectors (Sectors 1 to 5), higher productivity growth has little impact on GDP, but leads to significant increases in economy wide emissions. Productivity growth in these sectors reduces the relative price of output from these sectors (various forms of energy), which leads other sectors and final demand to substitute into energy and therefore raise emissions.

Figure 20 shows the impact of the United States sectoral productivity shocks on United States emissions and GDP in 2050. Interestingly, the relative importance of productivity growth to GDP and emissions varies between 2020 and 2050. In Sector Y, for example, further productivity growth results in further increases in GDP but the impact on emissions is almost unchanged. In Sector 12, the impact on emissions becomes larger than the impact on GDP.

**Figure 19: Percentage Change in US Emissions and Real GDP by 2020
For a 1 percent rise in US sector i productivity growth**

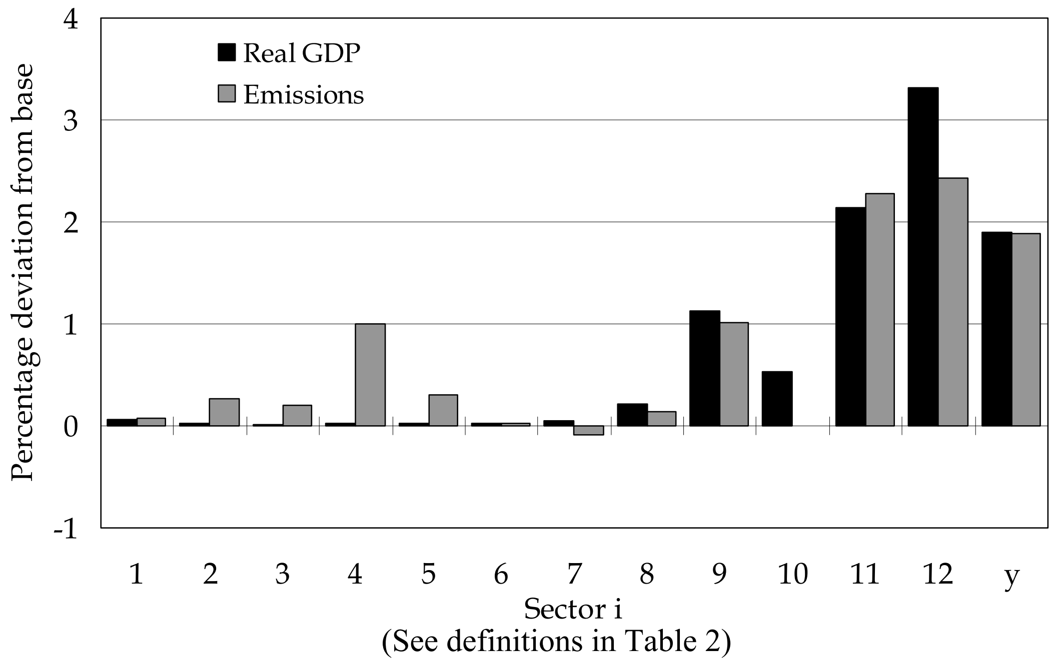
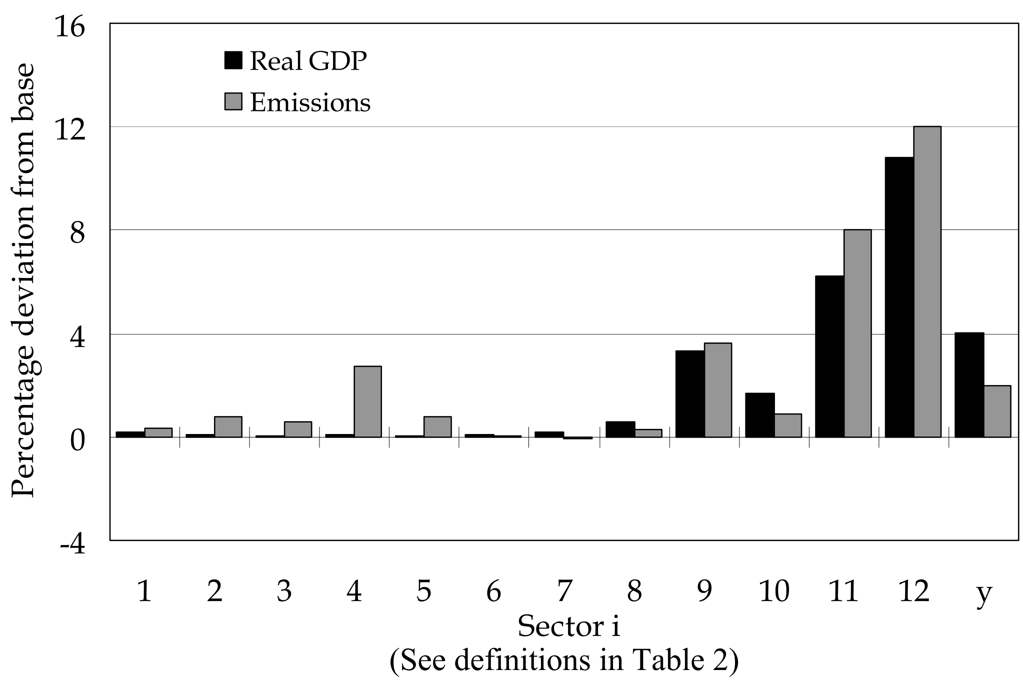


**Figure 20: Percentage Change in US Emissions and Real GDP by 2050
For a 1 percent rise in US sector i productivity growth**



Understanding the relationship between GDP and emissions requires breaking down the sources of GDP growth and the sources of changes in emissions. McKibbin, Pearce and Stegman (2004) use a simple example to demonstrate that it is possible for emissions and GDP to move in opposite directions and that the more important clean technology is as a driver of growth, the more likely it is that there will be a parameter set that will cause GDP and emissions to move in opposite directions.

The responses in Figures 19 and 20 also suggest that different sectors of the economy may be characterised by different emissions intensities. Differences in aggregate energy intensities across countries may result from differences in sectoral energy intensities and from differences in the structure of economic activity. The industry sector, which includes manufacturing, mining and construction, consumed around 30 percent of total world final energy consumption in 2002. The transport sector consumed over 25 percent. Other sectors accounted for the remainder. These other sectors include agriculture, services and the residential sector. In the OECD region, the agricultural sector accounted for 1.8 percent of OECD total final energy consumption in 2002. The industry sector accounted for 30 percent. A country with a large agricultural sector might be expected to consume less energy than a country with a high manufacturing sector. If the industrial structure of output is converging across countries then energy intensities may also eventually converge across countries. On the other hand, if sectoral energy intensities are different then convergence in the structure of economic activity will not be associated with aggregate energy intensity convergence. Likewise, convergence of sectoral energy intensities may not be associated with aggregate energy intensity convergence if economic structure differs across countries.

Figures 21, 22 and 23 contain summary measures of spread for the cross country distribution of output shares. The figures consider the shares of industry, services and agriculture in GDP. There does not appear to be any tendency for these shares to converge across countries when simple measures of spread (sigma convergence) are considered.

Figure 21: Summary Measures of Spread
Share of Industry in GDP (%)

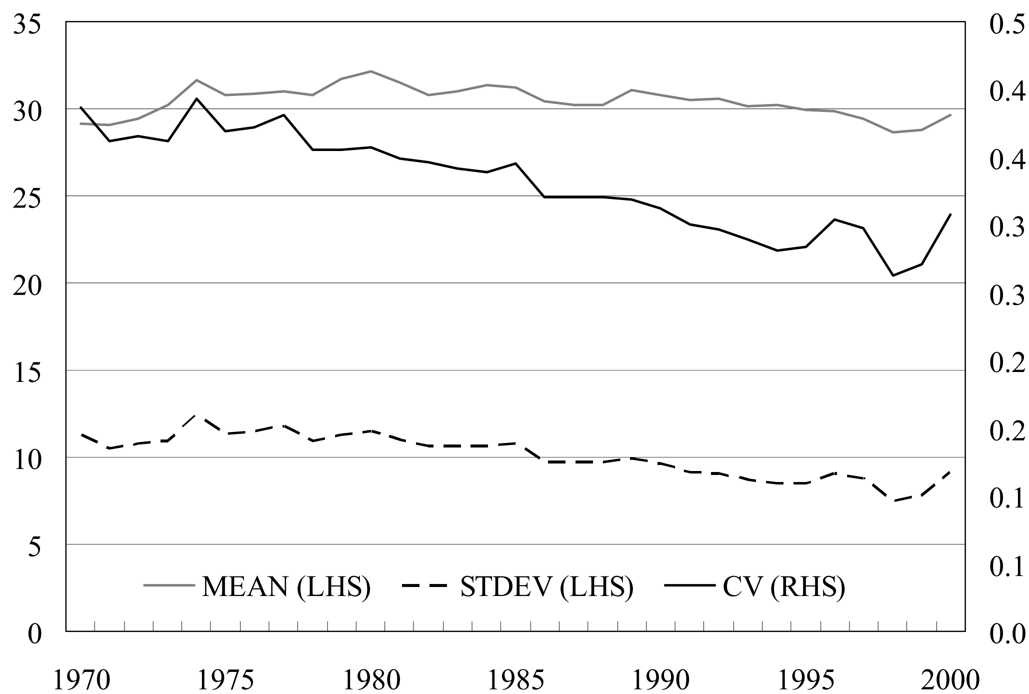


Figure 22: Summary Measures of Spread
Share of Services in GDP (%)

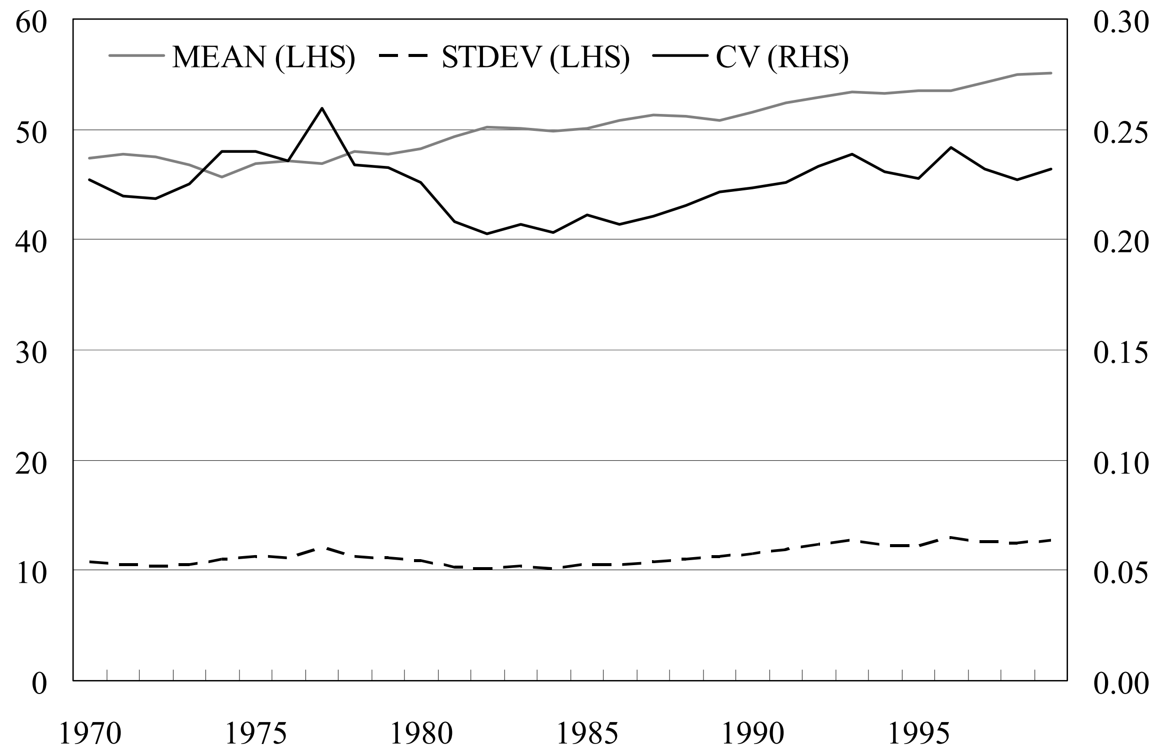
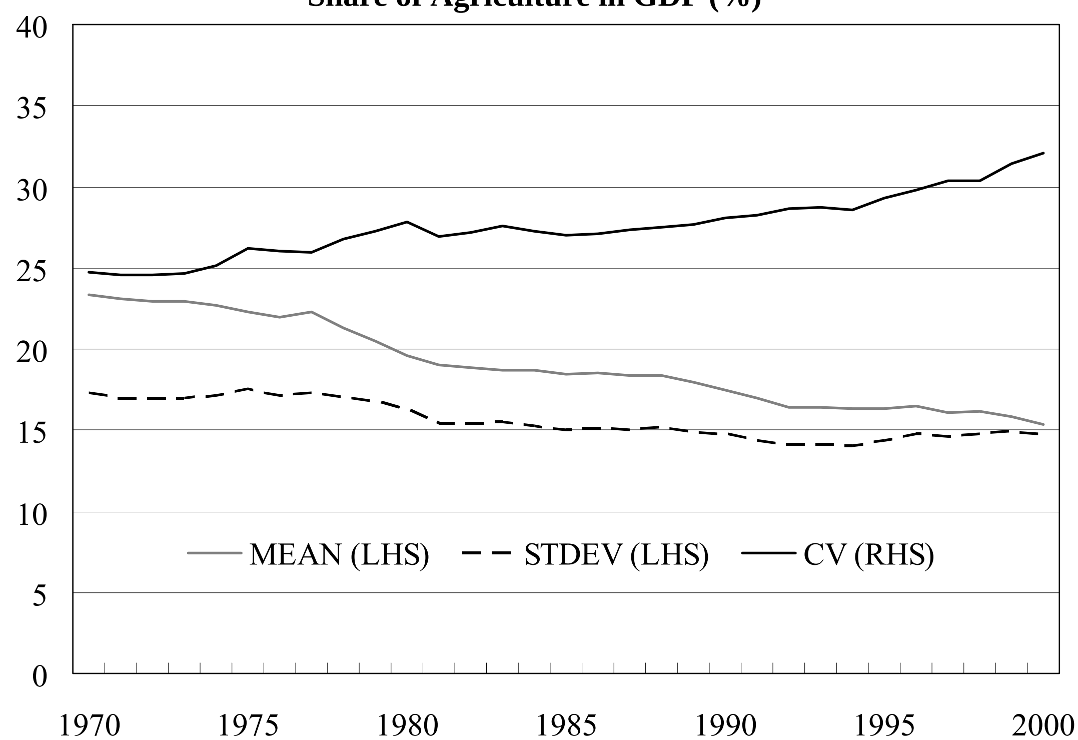
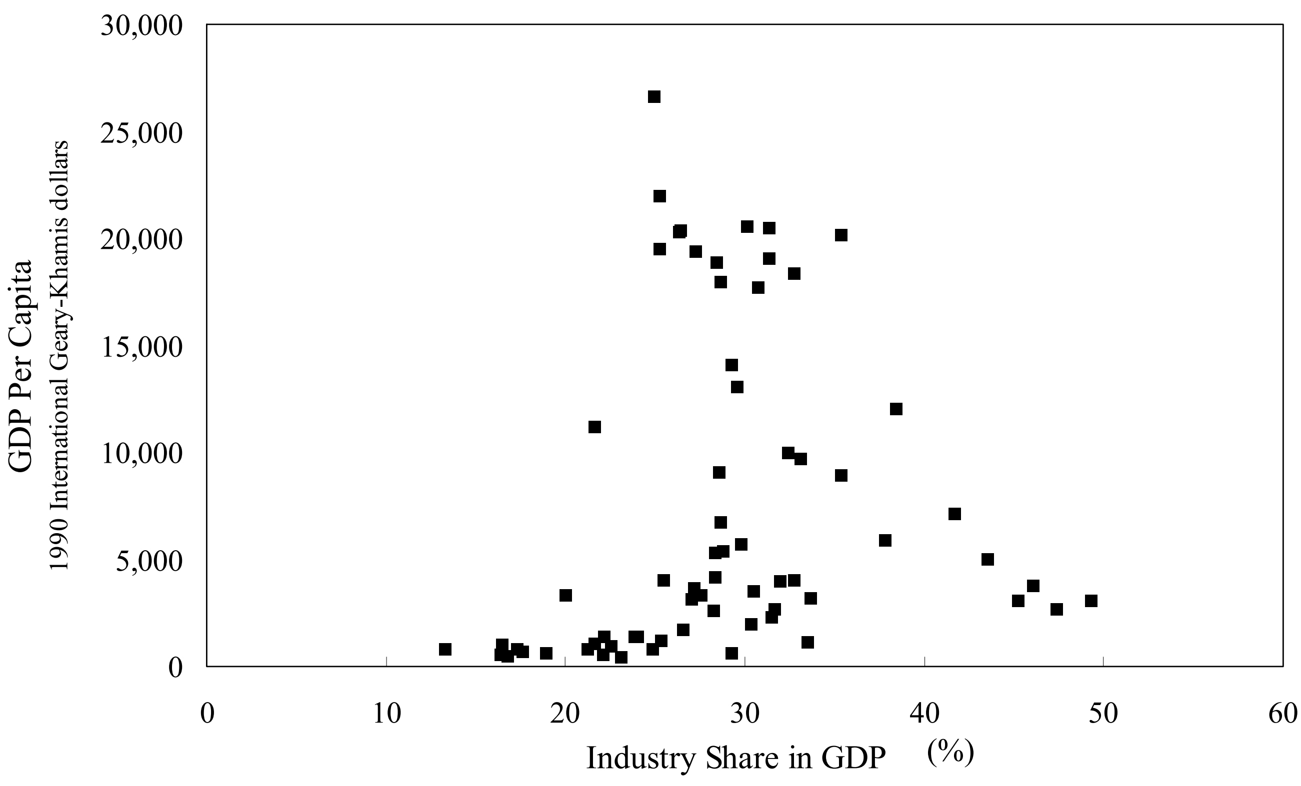


Figure 23: Summary Measures of Spread
Share of Agriculture in GDP (%)



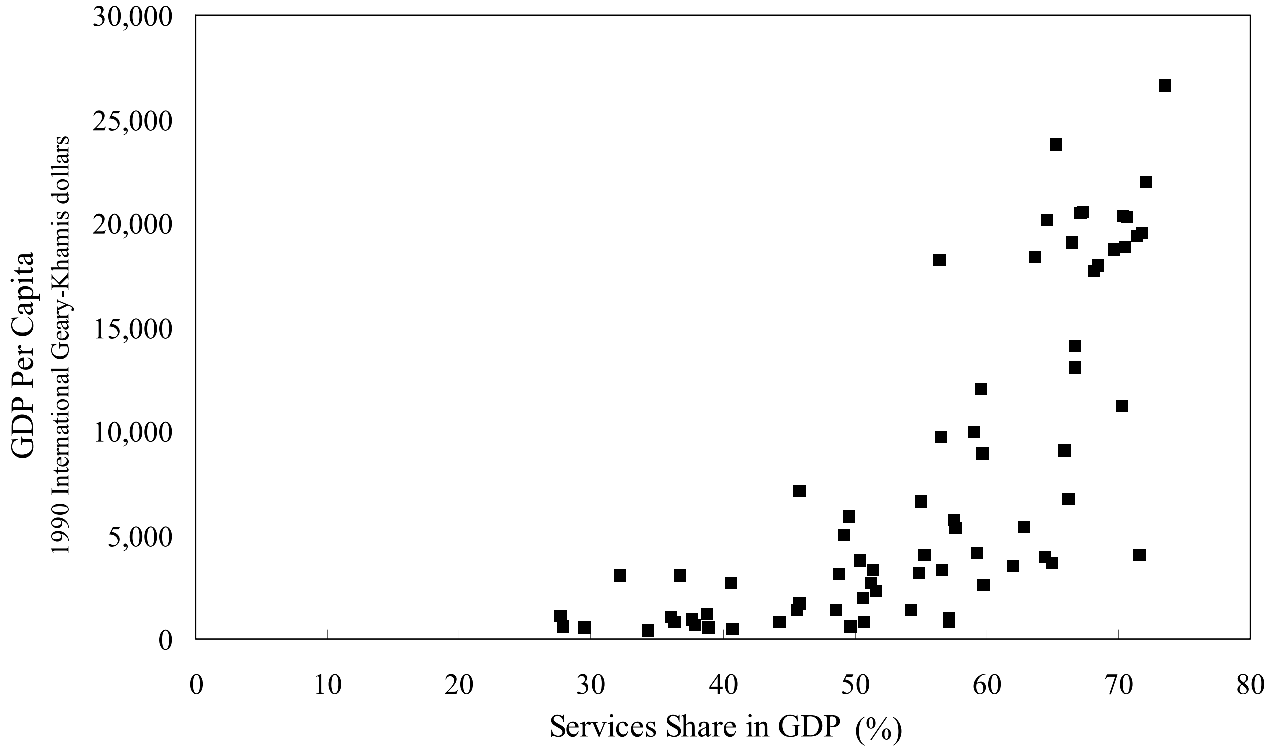
To investigate this idea further, Figures 24, 25 and 26 plot these output shares against GDP per capita. There does appear to be a relationship between the share of agriculture in GDP and GDP per capita and between the share of services in GDP and GDP per capita. There is no clear relationship for the industry sector. If GDP per capita levels converged across countries then agricultural and services shares may also converge. Figures 17 and 18 show little evidence of convergence in output shares, consistent with the majority of studies in income convergence that suggest there is no strong evidence for income per capita (unconditional) convergence across countries when a broad cross section of countries is considered.

Figure 24: GDP Per Capita and Industry Share in GDP (%), 1998



Source: WDI 2002, SourceOECD (2004), Maddison (2004)

Figure 25: GDP Per Capita and Services Share in GDP (%), 1998



Source: WDI 2002, SourceOECD (2004), Maddison (2004)

Figure 26: GDP Per Capita and Agricultural Share in GDP (%), 1998

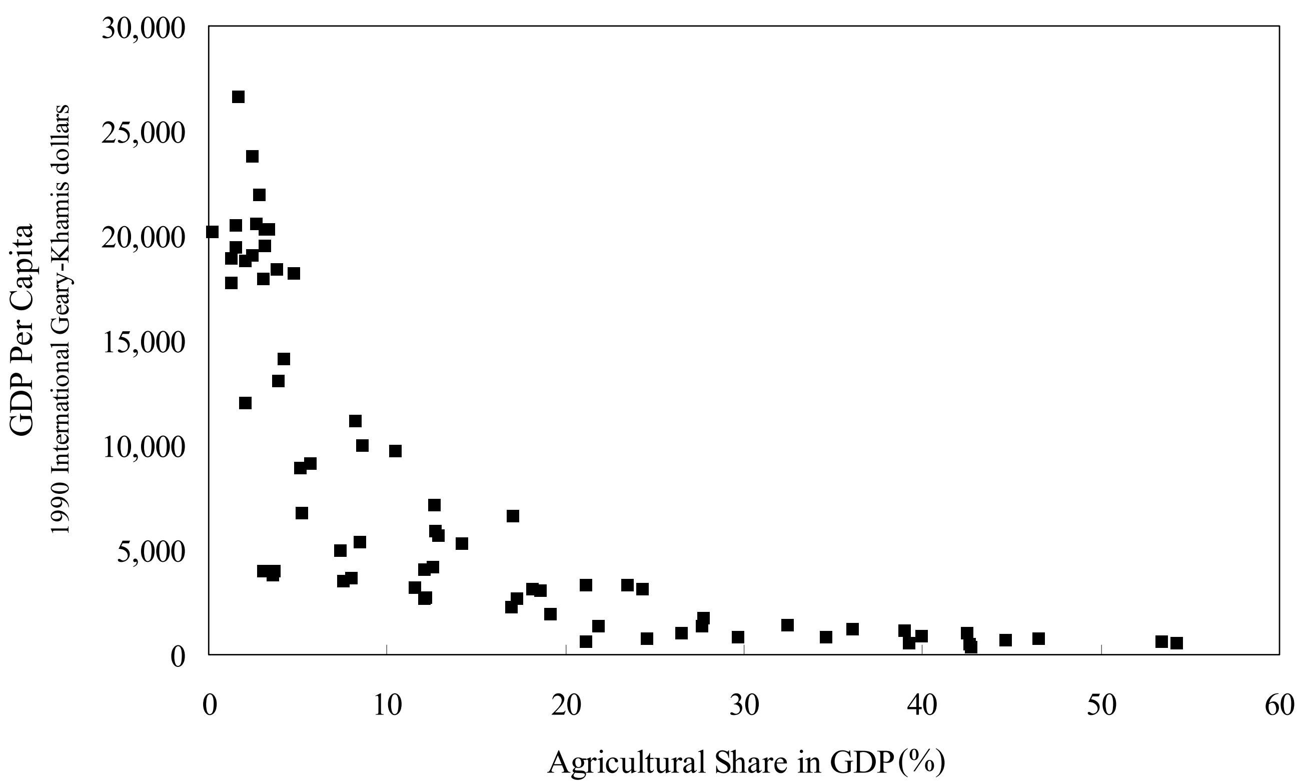
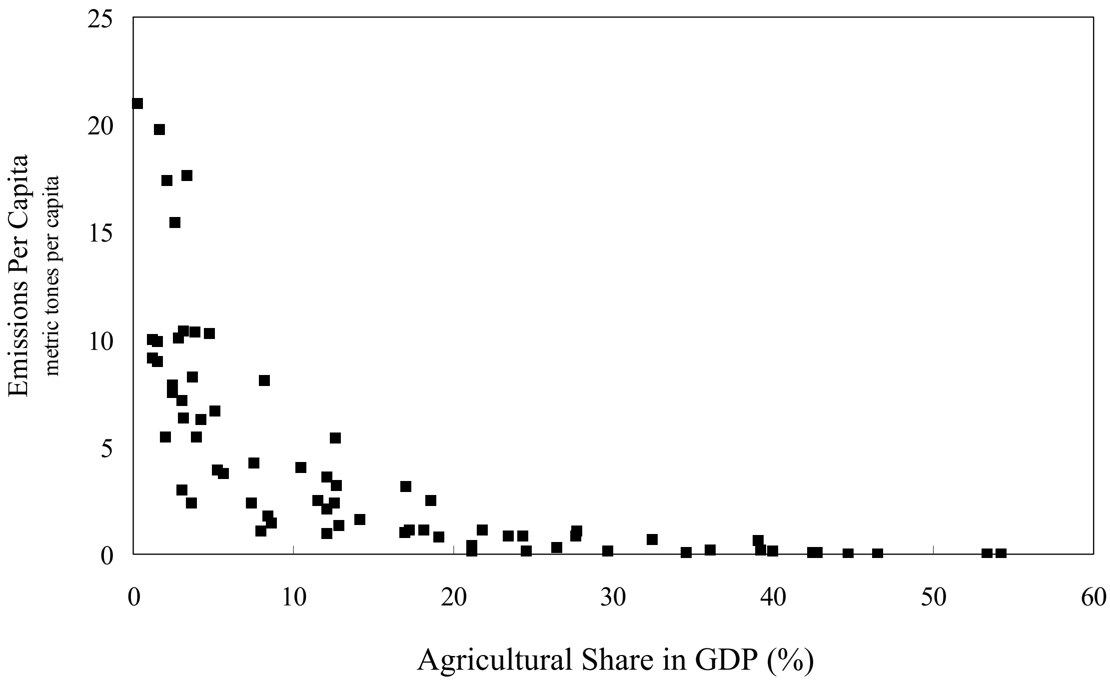
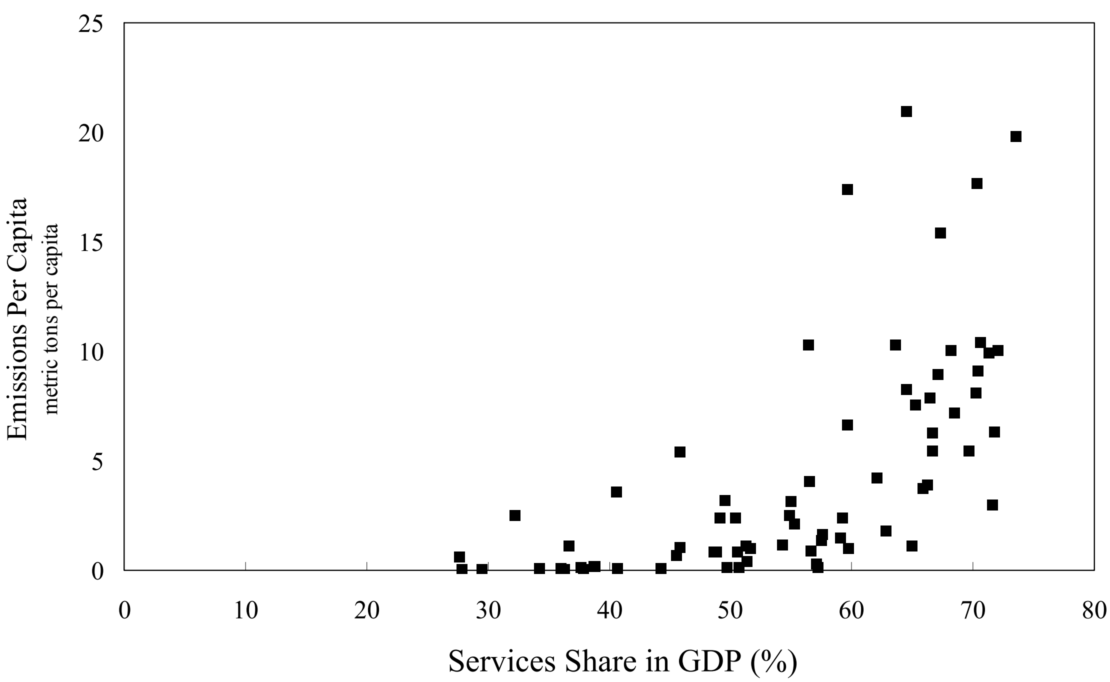


Figure 27: Emissions Per Capita and Agricultural Share in GDP (%), 1998



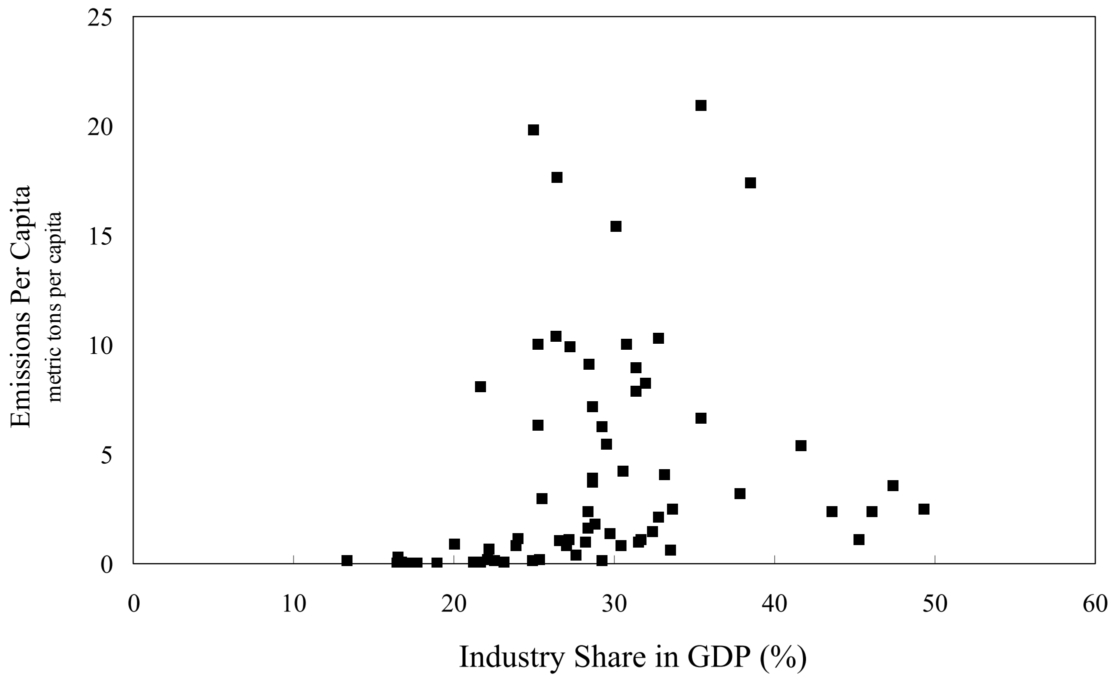
Source: WDI 2002, SourceOECD (2004), CDIAC (2004)

Figure 28: Emissions Per Capita and Services Share in GDP (%), 1998



Source: WDI 2002, SourceOECD (2004), CDIAC (2004)

Figure 29: Emissions Per Capita and Industry Share in GDP (%), 1998

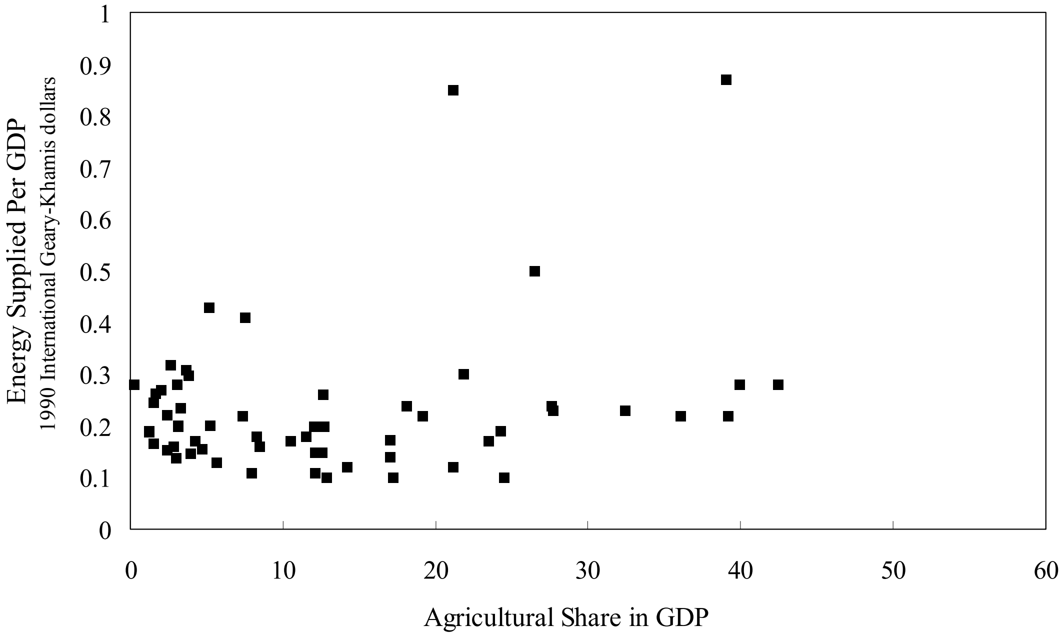


Source: WDI 2002, SourceOECD (2004), CDIAC (2004)

Figures 27, 28 and 29 plot output shares against emissions per capita. These graphs show a similar pattern to the GDP per capita scatter plots reflecting the positive relationship between GDP per capita and emissions per capita.

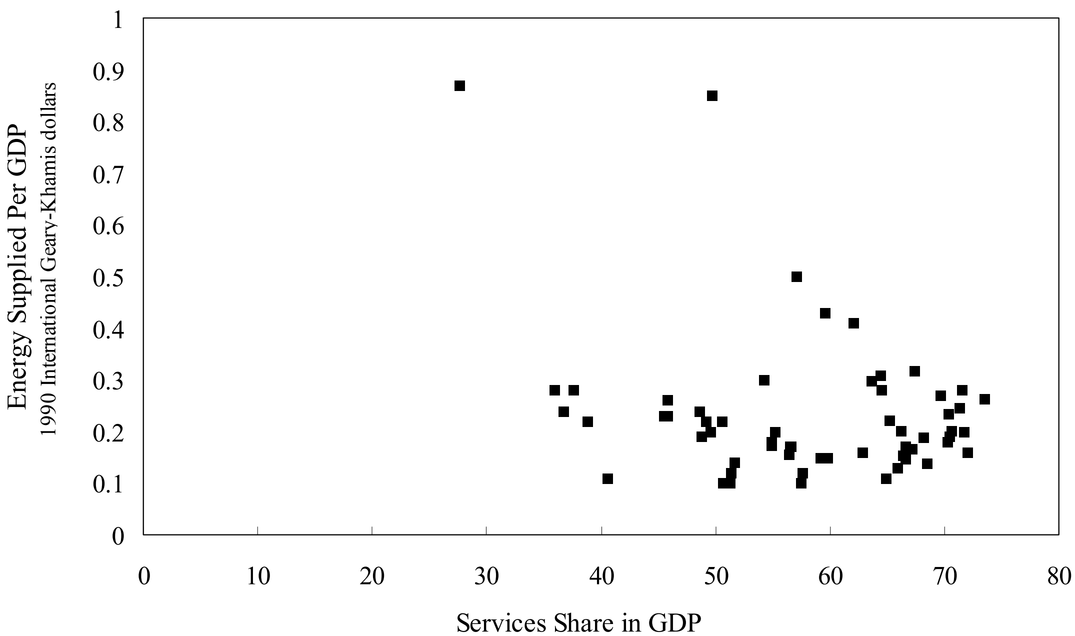
Figures 30, 31 and 32 plot output shares against the energy intensity of output (energy supplied per GDP). Figures 33, 34 and 35 plot output shares against the emissions intensity of energy supplied (emissions per energy supplied). These scatter plots do not show any clear relationship. This does not mean that differences in economic structure are not important in determining energy intensity differences across countries. It does highlight that there is no simple bi-variate relationship between these variables.

Figure 30: Energy Supplied Per GDP and Agricultural Share in GDP (%), 1998



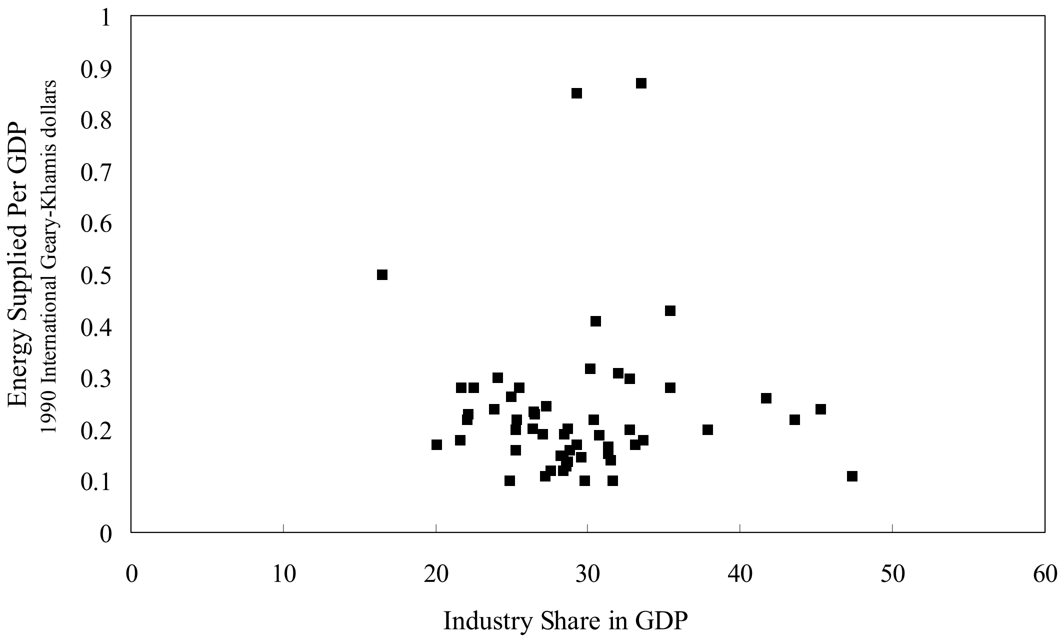
Source: WDI 2002, SourceOECD (2004), IEA (2004a, 2004b)

Figure 31: Energy Supplied Per GDP and Services Share in GDP (%), 1998



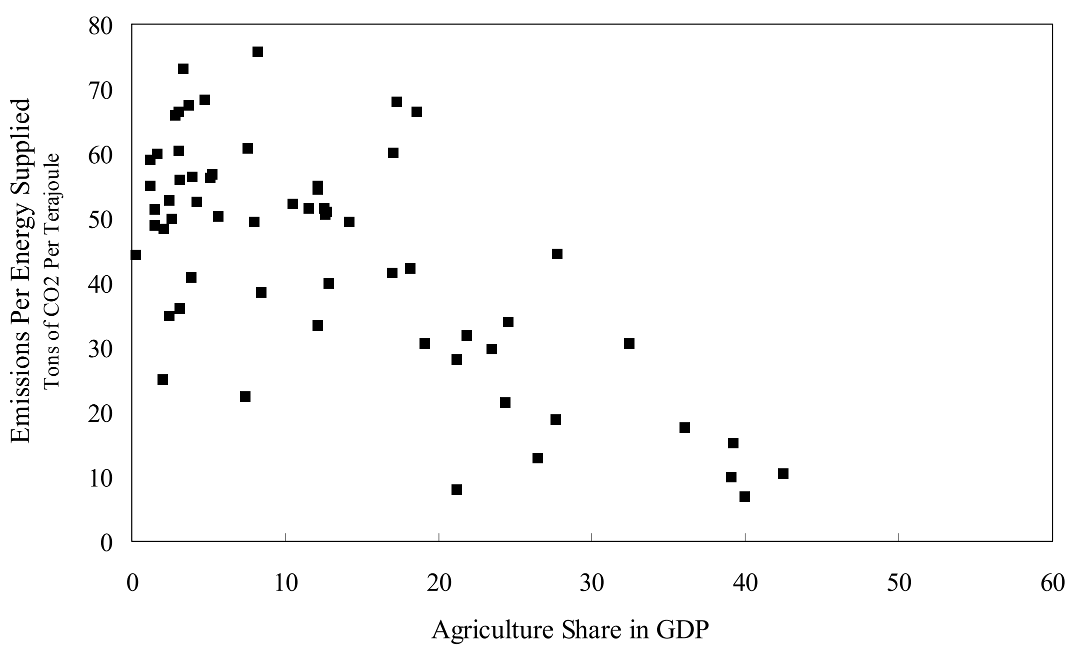
Source: WDI 2002, SourceOECD (2004), IEA (2004a, 2004b)

Figure 32: Energy Supplied Per GDP and Industry Share in GDP (%), 1998



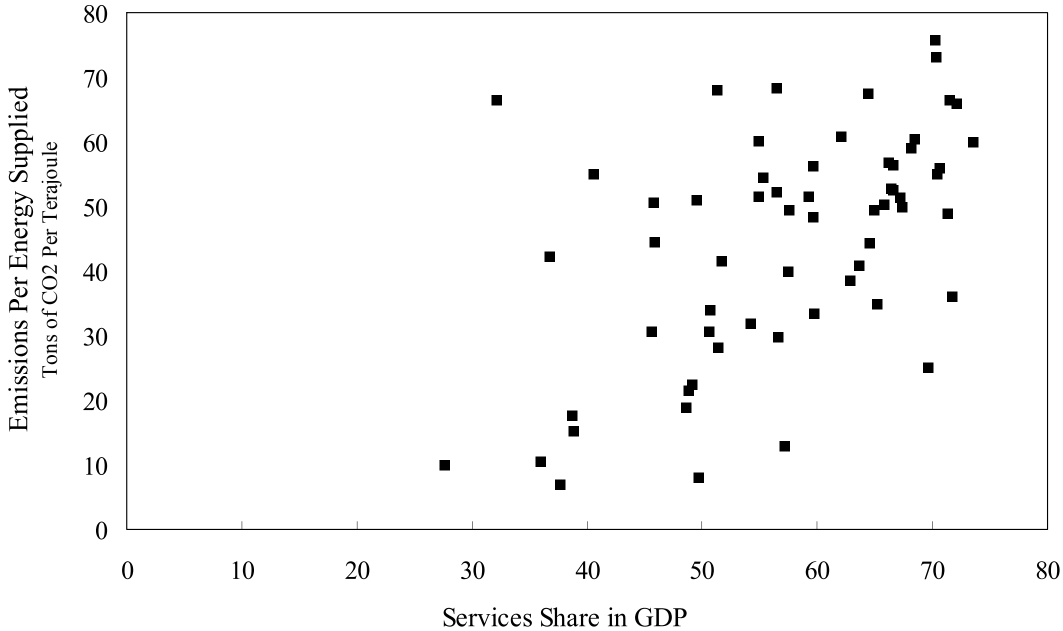
Source: WDI 2002, SourceOECD (2004), IEA (2004a, 2004b)

Figure 33: Emissions Per Energy Supplied and Agricultural Share in GDP (%), 1998



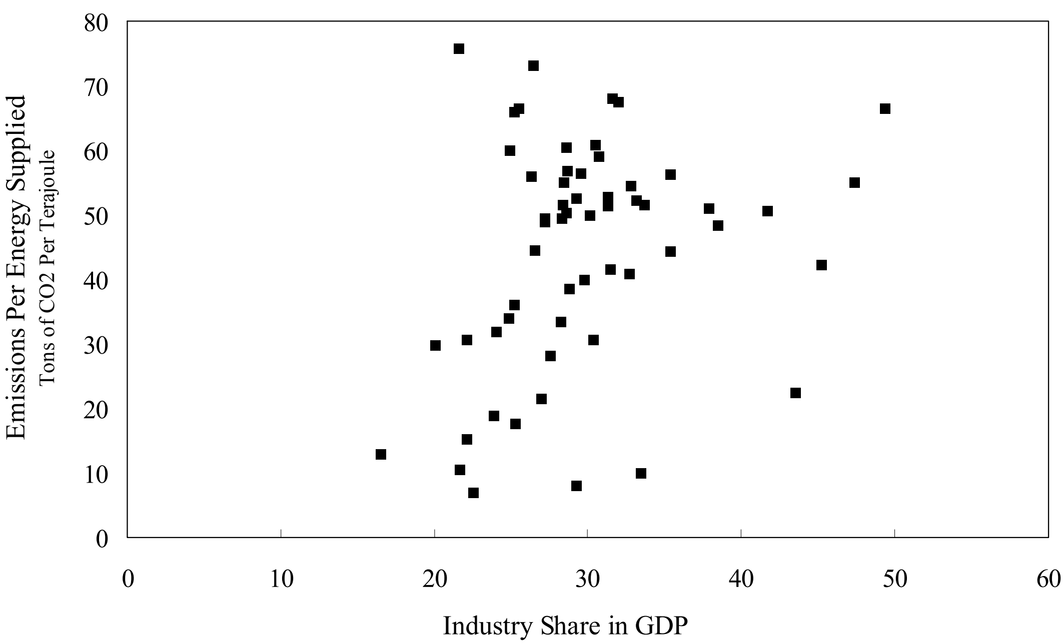
Source: WDI 2002, SourceOECD (2004), IEA (2003)

Figure 34: Emissions Per Energy Supplied and Services Share in GDP (%), 1998



Source: WDI 2002, SourceOECD (2004), IEA (2003)

Figure 35: Emissions Per Energy Supplied and Industry Share in GDP (%), 1998



Source: WDI 2002, SourceOECD (2004), IEA (2003)

This analysis of emissions and economic activity suggests that economic activity is an important determinant of emissions per capita. There appears to be strong relationships between the level of economic activity and emissions per capita and between the structure of economic activity and emissions per capita. There is no simple bi-variate relationship between GDP per capita and the energy intensity of output and between output shares and the energy intensity of output. It is likely that energy intensity is related to the structure of an economy but it is also likely to depend on other factors such as relative prices, technology and institutional arrangements.

4.2. Differences in Fossil Fuel Endowments

Table 3 lists a number of energy and emissions rankings in 2001 according to the International Energy Agency (2003). Table 4 lists those countries with the highest fossil fuel reserves as listed by the Energy Information Administration (2004). The International Energy Agency lists Qatar as the country with highest levels of energy supplied and emissions per capita. Qatar's natural gas reserves rank third after Russia's and Iran's. The IEA lists Iraq as the country with highest levels of energy supplied and emissions per GDP. Iraq's proven oil reserves rank third after Saudi Arabia's and Canada's and the EIA suggests that Iraq may hold much more undiscovered oil in unexplored areas of the country. Iraq's natural gas reserves are ranked as the tenth largest.

Table 3: International Energy Agency Rankings in 2001 (IEA, 2003)

Total Primary Energy Supplied Per Capita	CO2 Emissions Per Capita
1. Qatar	1. Qatar
2. Iceland	2. Kuwait
3. United Arab Emirates	3. United Arab Emirates
4. Bahrain	4. Bahrain
5. Luxembourg	5. United States
6. Kuwait	6. Luxembourg
7. Canada	7. Australia
8. United States	8. Canada
9. Singapore	9. Gibraltar
10. Netherlands Antilles	10. Netherlands Antilles

Total Primary Energy Supplied Per GDP	CO2 Emissions Per GDP
1. Iraq	1. Iraq
2. Nigeria	2. DPR of Korea
3. Qatar	3. Uzbekistan
4. Uzbekistan	4. Qatar
5. Zambia	5. Kuwait
6. United Rep. of Tanzania	6. Turkmenistan
7. Trinidad and Tobago	7. Russia
8. DPR of Korea	8. Bahrain
9. Turkmenistan	9. Ukraine
10. Ukraine	10. Libya

Iceland is listed as the second highest supplier of energy per capita. Although Iceland is not listed in Table 2, its energy supply is related to its natural endowments. According to the IEA (2004a), 55 percent of Iceland's total primary energy supplied in 2002 was generated from geothermal resources and the combination of geothermal and hydroelectric energy accounted for over 72 percent of total energy supplied.

Table 4: Fossil Fuel Reserves (EIA, 2004)
World Rankings and Percent of Total

	Crude Oil Reserves		Natural Gas Reserves
1.	Saudi Arabia (22%)	1.	Russia (31%)
2.	Canada (15%)	2.	Iran (15%)
3.	Iraq (9%)	3.	Qatar (9%)
4.	United Arab Emirates (8%)	4.	Saudi Arabia (4%)
5.	Kuwait (8%)	5.	United Arab Emirates (4%)
6.	Iran (7%)	6.	United States (3%)
7.	Venezuela (6%)	7.	Algeria (3%)
8.	Russia (5%)	8.	Venezuela (3%)
9.	Libya (2%)	9.	Nigeria (2%)
10.	Nigeria (2%)	10.	Iraq (2%)

	Recoverable Coal
1.	United States (25%)
2.	Russia (16%)
3.	China (12%)
4.	India (9%)
5.	Australia (8%)
6.	Germany (7%)
7.	South Africa (5%)
8.	Ukraine (3%0
9.	Kazakhstan (3%)
10.	Poland (2%)

Clearly natural endowments are an important determinant of country emission and energy variables. The rankings in Tables 3 and 4 however, suggest that natural endowments are not the sole determinant of these variables. There are countries listed in Table 3 that do not appear in Table 4 and vice versa.

4.3. The Structure of Energy Use

Fossil fuel combustion is the primary source of greenhouse gas emissions. The fuel mix of energy supplied is therefore likely to be a determinant of a country's CO_2 emissions. Of course, CO_2 emissions will also depend on the quantity of total energy supplied, but for two countries with similar energy supplies, differences in fossil fuel emissions are likely to be related to differences in the contribution of alternative energy sources. This in turn is likely to depend on natural endowments. This relationship was highlighted by the example of Iceland in the previous section. Although Iceland's energy supplied per capita is the world's third highest, fossil fuel emissions per capita in Iceland do not rank in the world top ten or even in the world top twenty because over 70 percent of Iceland's energy supply is sourced from renewable energy supplies. This situation is possible because of geothermal sources in Iceland.

If there is evidence that the structure of energy supplied is converging across countries, this may provide some support for the inclusion of emissions per capita convergence assumptions. Even if the structure of energy supplied across countries converges, differences in emissions per capita across countries are likely to persist due to differences in the quantity of energy supplied and other country specific factors, but empirical evidence of energy structure convergence may justify some modified convergence assumptions that could be useful in the face of the extensive uncertainty that surrounds emissions projection models. Figures 36 and 37 show the contribution of Coal, Oil, Gas and Other fuel sources to total primary energy supplied for the world's major regions in 1971 and 2002. There does not appear to be a strong tendency towards convergence in these shares.

Figure 36: Fuel Shares in Total Primary Energy Supplied - 1971

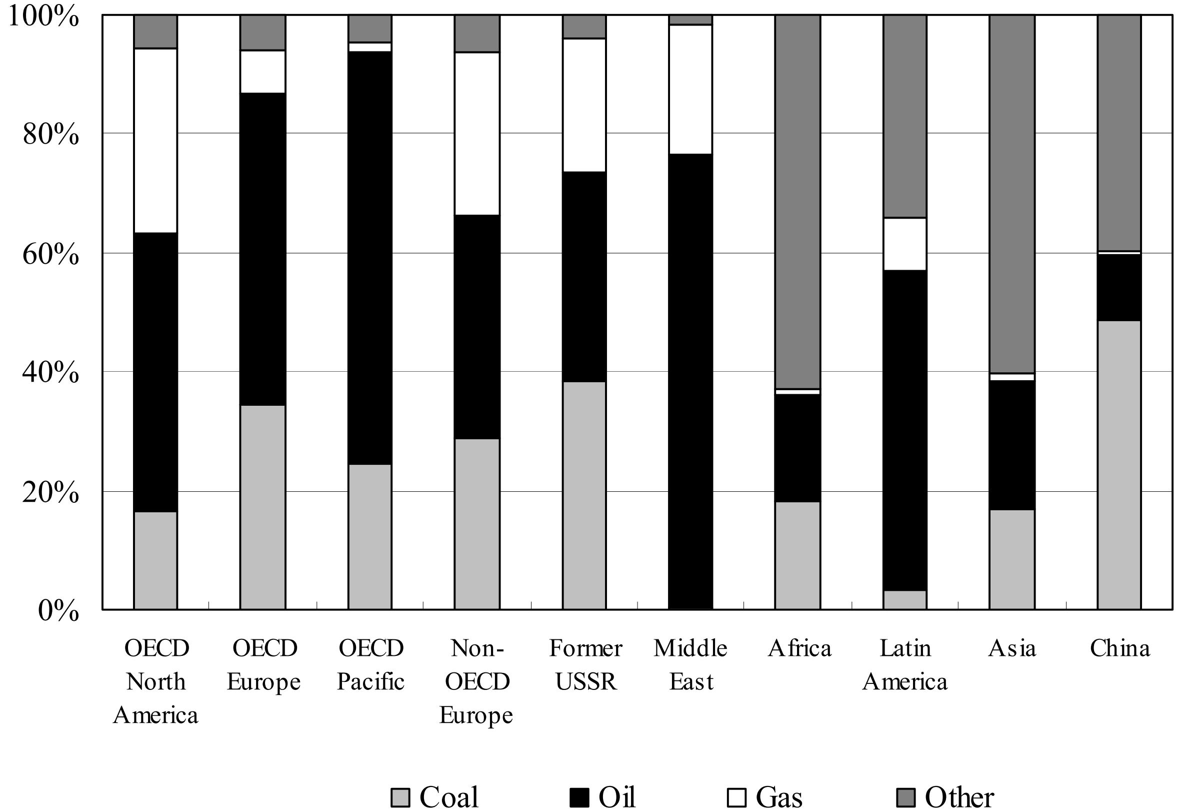
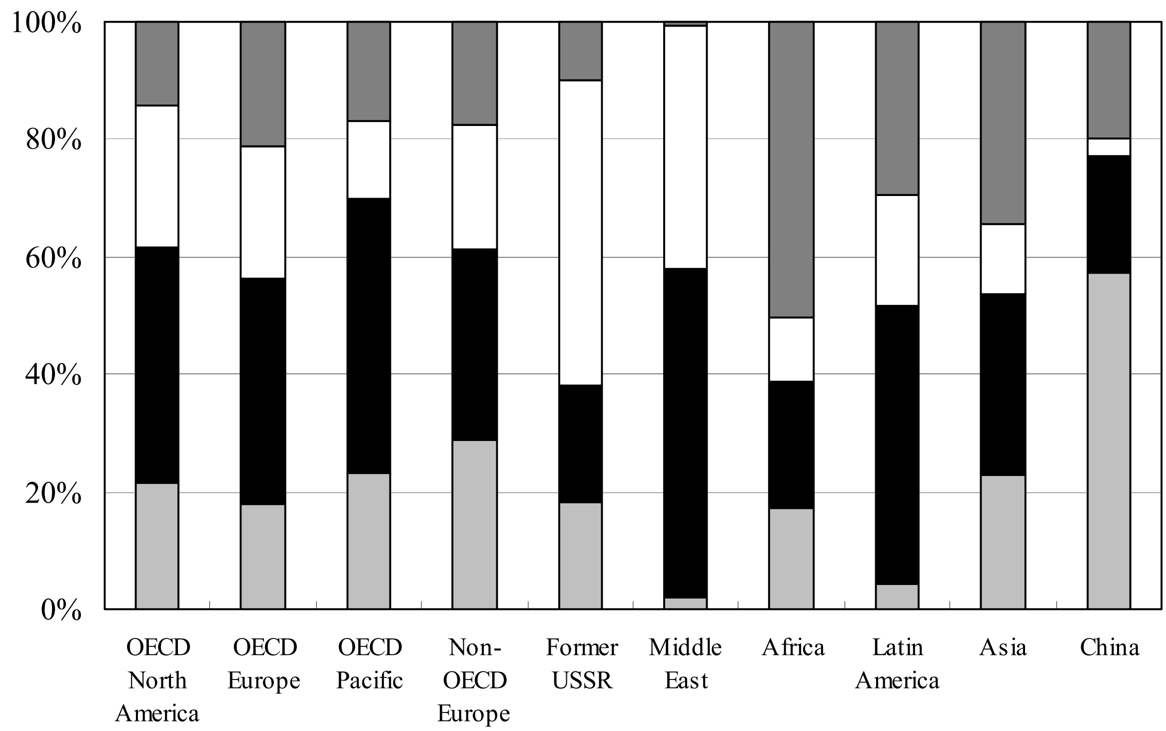
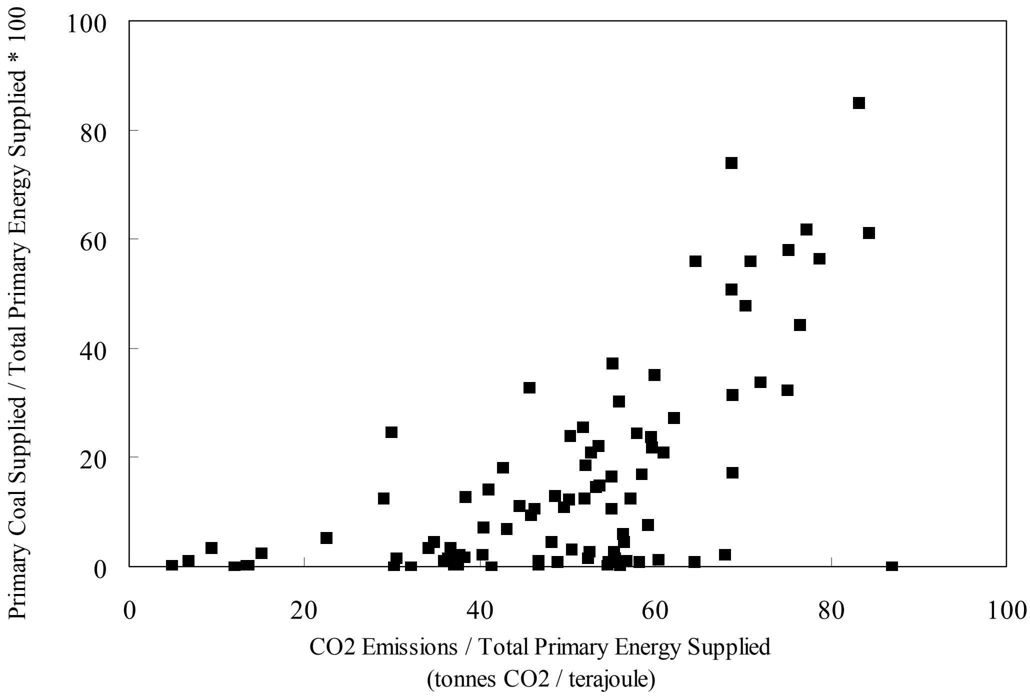


Figure 37: Fuel Shares in Total Primary Energy Supplied - 2002



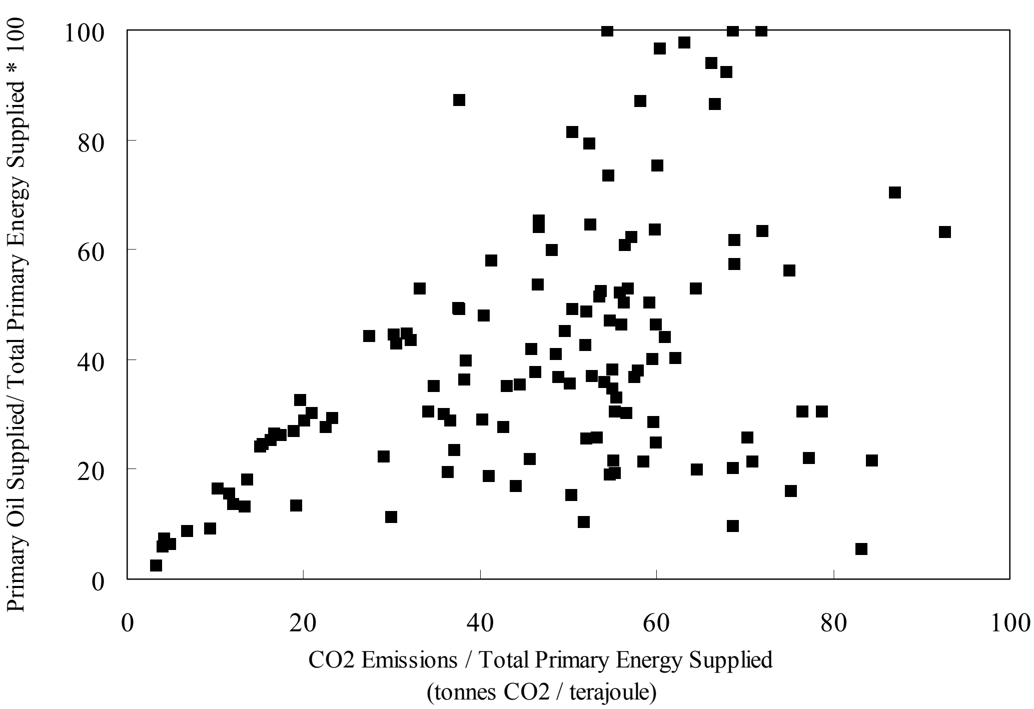
Source: IEA 2004a, 2004b

Figure 38: Percentage of Coal in Total Primary Energy Supplied and CO_2 Emissions Per Total Primary Energy Supplied - 2001



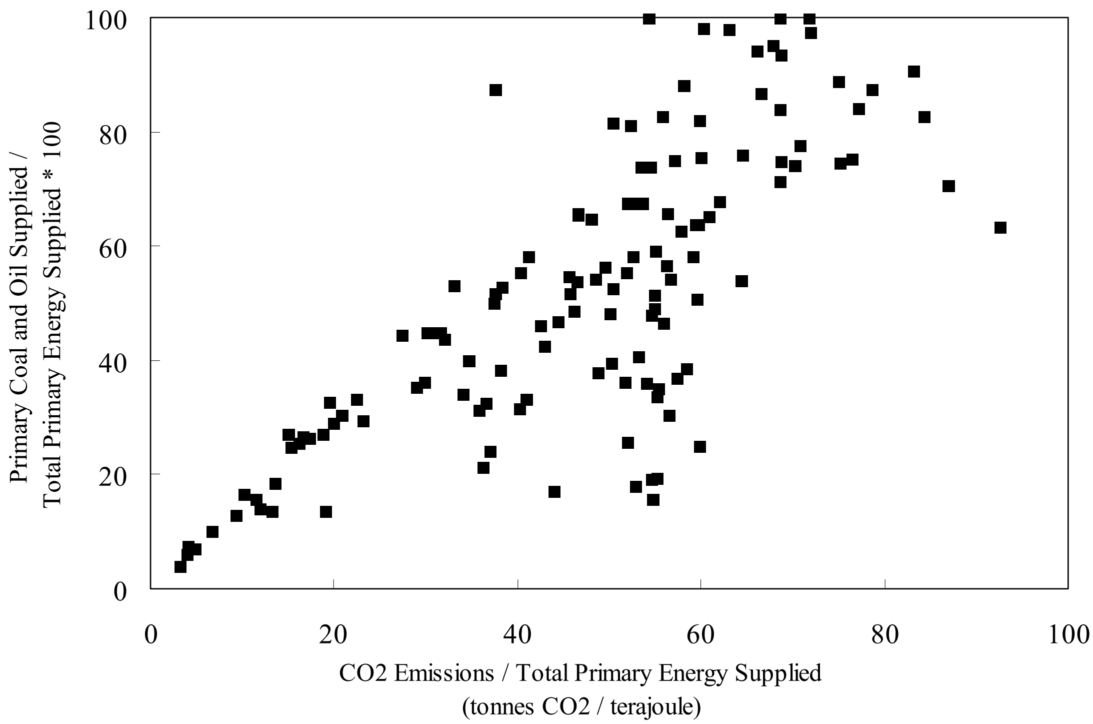
Source: IEA 2004a, 2004b, 2003

Figure 39: Percentage of Oil in Total Primary Energy Supplied and CO_2 Emissions Per Total Primary Energy Supplied - 2001



Source: IEA 2004a, 2004b, 2003

Figure 40: Percentage of Coal and Oil in Total Energy Supplied and CO_2 Emissions Per Total Energy Supplied - 2001



Source: IEA 2004a, 2004b, 2003

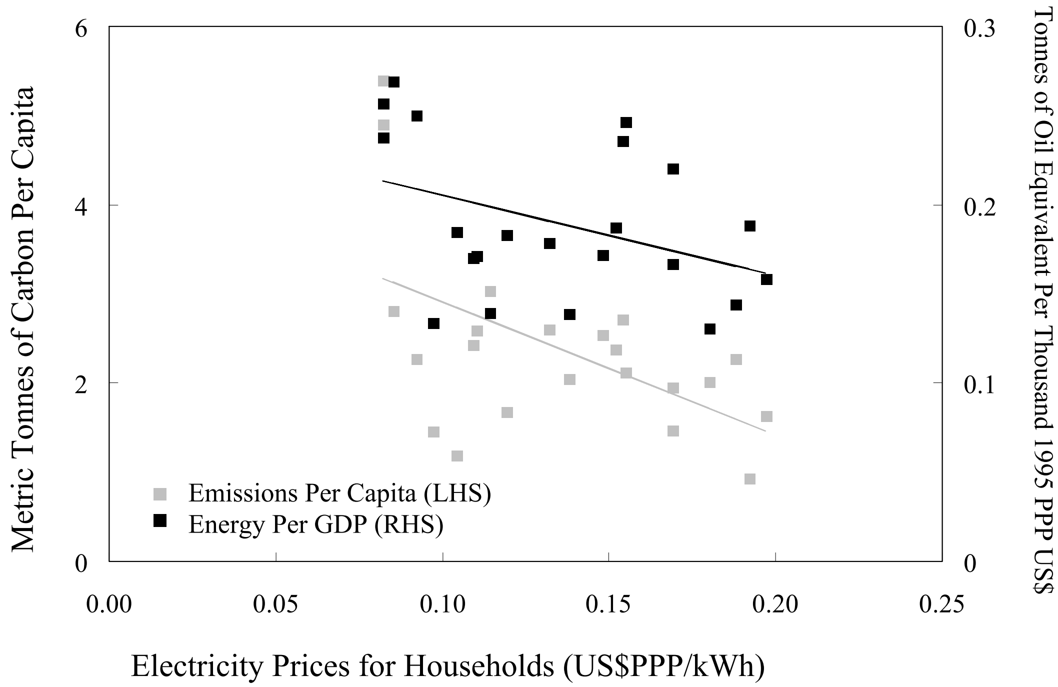
Figures 38 and 39 respectively plot the contribution of coal and oil to total primary energy supplied against the ratio of CO_2 emissions to total primary energy supplied. Both figures suggest that there is a positive relationship between these variables. Figure 40 plots the combined contribution of coal and oil to total primary energy supplied against the ratio of CO_2 emissions to total primary energy supplied. This figure shows a strong positive relationship. The emissions intensity of energy supplied is therefore related to the contribution of alternative fuel sources. This in turn is related to natural endowments. The quantity of energy supplied is related to economic activity. Differences in the level of economic activity as well as differences in the structure of economic activity lead to differences in energy supplied and therefore differences in emissions.

4.4. ***Energy Prices and Emissions Per Capita***

Energy prices, changes in prices over time and differences in prices across countries are likely to impact emissions per capita in a number of ways. There is evidence that the oil price shocks of 1973 and 1981 led to a reduction in the energy intensity of output (IEA, 2004c). The impact of these price shocks was highlighted by Figure 17. The effect of higher oil prices on emissions, however, also depends on how the relative prices of alternative fuel sources respond and on the ability of countries to adjust the fuel composition of energy supplied. Furthermore, changes in oil prices are likely to affect economic growth which in turn impacts energy use and emissions.

Oil prices are not the only relevant price factors. Differences in the fuel composition of energy supplied, differences in government energy policy and differences in trade practices and transport costs are likely to affect the price of energy and therefore its use. The impact of all of these factors on emissions per capita is difficult to measure and the individual (sometimes offsetting) effects are difficult to isolate. Changes in price differentials will induce differences in the composition of energy usage and the energy intensity of output. These differences affect the distribution of emissions per capita, as described above. In general, a lower relative energy price would encourage higher energy use and therefore emissions. The impact of energy use on emissions, however, critically depends on the composition of energy supplied. If a large share of energy is generated from relatively cheap renewable sources then low prices may be associated with low emissions. Figure 41 plots the energy intensity of output and emissions per capita against electricity prices in the small number of OECD countries for which a consistent series is available.

Figure 41: Electricity Prices, Energy Supplied and Emissions, 2000



Source: IEA 2004a, 2004d, CDIAC 2004

There is a weak negative relationship between electricity prices and energy supplied per unit of GDP and between electricity prices and emissions per capita. A larger cross section would be more informative on the relationship between these variables.

*4.5. **Summary***

This section has highlighted key variables that determine emissions per capita. There is a strong relationship between economic development and emissions per capita. Higher levels of income per capita lead to increased energy consumption which in turn is generally associated with higher emissions. Cross country differences in GDP per capita are also associated with differences in economic structure, such as the share of agriculture in economic output, which affects the energy intensity of output. Natural endowments play an important role in determining the structure (fuel mix) of energy supplied which is a key determinant of the emissions intensity of energy supplied.

5. Beta (β) Convergence in Emissions Per Capita

The analysis in this paper has been designed to provide a statistical examination of the distribution of emissions per capita and the tendency, if any, towards convergence. The examination of emissions per capita was extended to examine key macroeconomic and energy variables that determine emissions across countries and over time. The analysis is not based on a theoretical model of per capita emissions convergence and the results are not dependent on assumptions of model specification.

It would, in fact, be difficult to derive a theoretical model in which emissions per capita converge. If greenhouse gas emissions resulted primarily from individual activities such as the use of automobiles and private electricity consumption then a theoretical model of emissions per capita convergence could be based on economic development. As outlined in the previous section, however, the distribution of emissions is related to the structure of a country's economy and its natural endowments, development level and comparative advantage in the production of various goods.

This section provides a basic cross sectional analysis of the existence of beta convergence in emissions per capita. The section is included for completeness and for the benefit of readers who are familiar with the growth literature on convergence. The section begins by providing a general description of beta convergence and the relationship between beta convergence and the distributional analysis in Section 1. The implication of these results for model projections is then considered.

As outlined in Section 1, there are four broad approaches to convergence analysis in the economics growth literature: beta convergence, sigma convergence, time series (cointegration) analysis, and distributional analysis. The existence of beta convergence in income per capita has been given considerable attention in the literature and the results of empirical examinations have generated extensive debate.

Beta convergence in the growth literature 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. That is, a situation where poor countries tend to grow faster than richer countries.

Beta convergence in income per capita is generally examined by estimating the cross sectional equation:

$$\ln(y_{i,T}/\,y_{i,0}) = a + b\ln(y_{i,0}) + c\,X_i + e_i \qquad (4)$$

where $y_{i,0}$ is the income per capita level in the initial period and $y_{i,T}$ is the income per capita level in the final period.

A negative *b* coefficient implies beta convergence. The variables X_i are used as proxies for a country's steady state level of income per capita. The inclusion of these variables implies a *conditional* convergence analysis. The implication of beta convergence 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 Sala-i-Martin and Barro (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). Sala-i-Martin (1996a) uses three simple diagrams to demonstrate this point. Consider Figure 42. Panel 1 shows a situation in which there is beta convergence and sigma convergence in the variable of interest, *Y*. The country with the lower initial level, *B,* experiences higher growth than *A*.

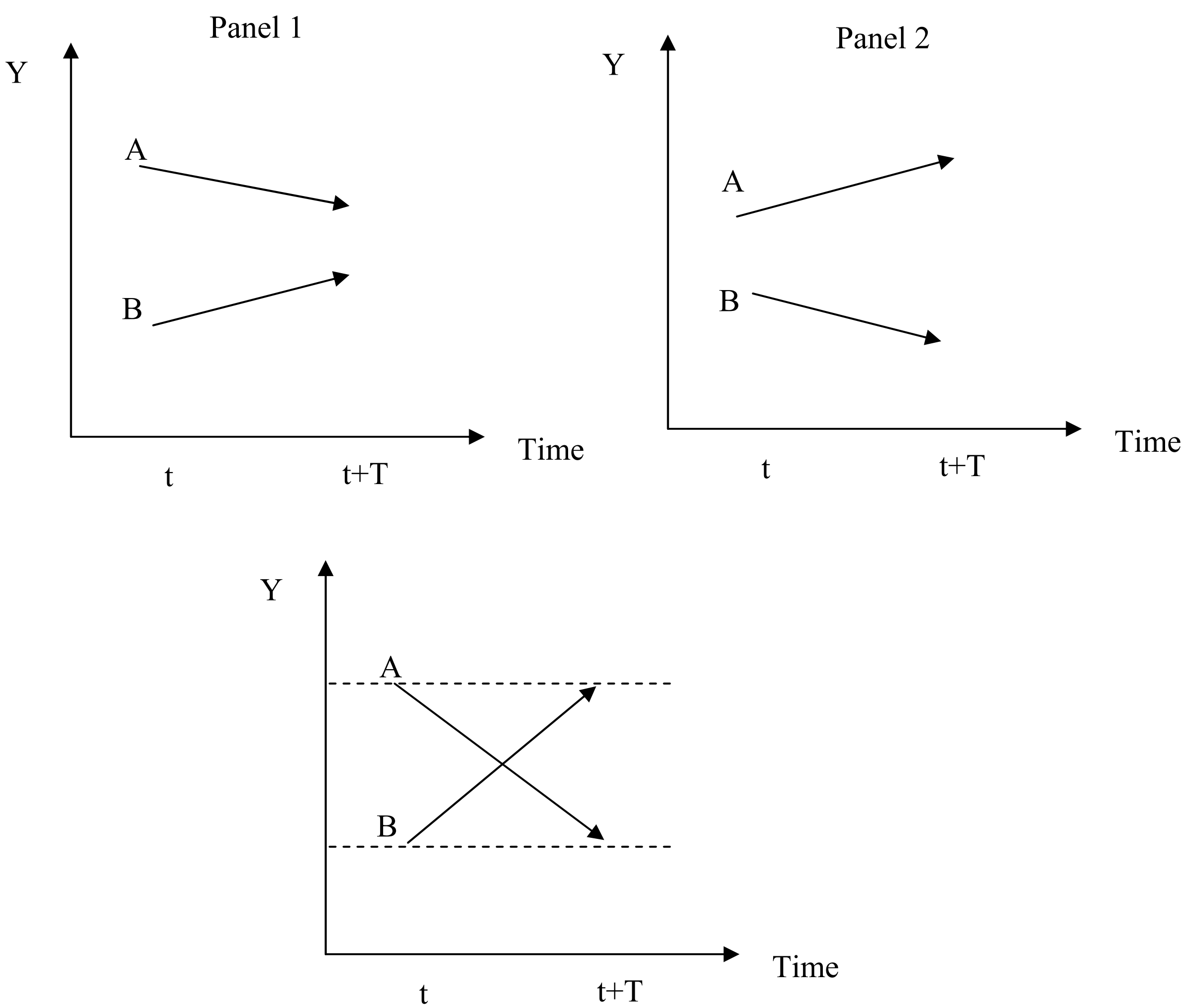
Panel 2 shows a situation in which there is a lack of beta convergence and this is associated with a lack of sigma convergence. In Panel 3 there is beta convergence. A higher growth rate is associated with a lower initial level, but there is no sigma convergence. In this example, the dispersion is the same in the two time periods.

It is possible, therefore, for beta convergence to exist without sigma convergence. This has led some researchers to question the value of analyses that attempt to measure the existence of beta convergence and to argue 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). Quah (1995a) however argues that cross sectional regression approaches to 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 the dynamic distributional approach to convergence analysis undertaken in Section 1 which provides information on both dispersion and mobility. 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).

Figure 42: The relationship between sigma and beta convergence



In Section 1 convergence in emissions per capita was analysed using two approaches to convergence: σ-convergence and distributional analysis. As described above, the existence of σ-convergence is a relatively strong result that implies there is also beta convergence. The absence of σ-convergence, as identified in Section 1 with respect to emissions per capita, does not imply that beta convergence is not a feature of the data. With respect to income per capita, beta convergence may be of interest, even in the absence of sigma convergence, because income per capita convergence is often discussed in reference to equality. Furthermore, estimation of the beta convergence regression equation allows parameters of interest in neoclassical growth theory to be investigated. The beta regression is used to test hypotheses of interest in growth economics.

The analysis in this paper is interested in convergence as an assumption included in projection models and in most cases σ-convergence will be the concept of interest. An analysis of beta convergence is included here to highlight the alternative approaches to convergence analysis and the implications of using alternative convergence definitions.

The analysis in this section is based on a cross section of 91 countries (detailed in the Appendix). In Section 1, it was argued that the level of emissions per capita or the level relative to the mean were the most appropriate series for analysing convergence in emissions per capita. In this section the standard beta regression from the growth literature is estimated:

$$\ln(epc_{i,2000}/\, epc_{i,1950}) \;=\; a \;+ b_1 \ln(epc)_{i,1950} \;\; + e_i \qquad (5)$$

where $epc_{i,2000}$ is country i's emission per capita rate in 2000 and $epc_{i,1950}$ is country i's emission per capita rate in 1950.

The model is specified linearly in logs for ease of estimation and interpretation. The logarithmic transformation is also used to reduce the amount of skewness in the data. The b_1 coefficient is used to examine the existence of *unconditional* beta convergence.

Figure 43 plots the dependent variable in Equation (5), the growth rate of emissions per capita over the period 1950 to 2000, against the log level of emissions per capita in 1950, along with the estimated fitted values from regression Equation (5) for the full sample of 91 countries as well as for a restricted OECD sample.

The coefficient estimates for Equation (5) are contained in Table 5.

Figure 43: The Growth Rate and Level of Emissions Per Capita

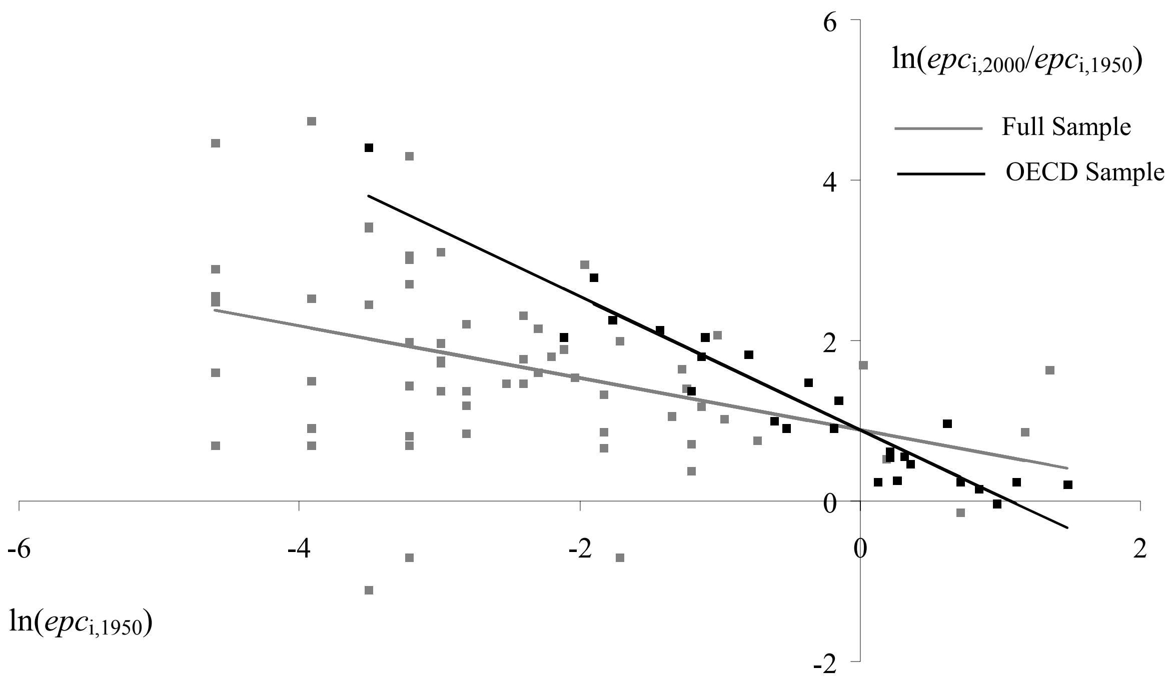


Table 5: Cross-Sectional Regression Estimates

	Full Sample	**OECD Sample**
A	0.89 (0.16)*	0.86 (0.07)*
B	-0.32 (0.06)*	-0.83 (0.06)*
R^2	0.23	0.89
Obs	91	26

Standard errors are in brackets. * indicates significance at the 5% level.

Estimation of Equation 5 demonstrates the correlation between the growth rate in emissions per capita and the initial level.[3] The information in Figure 43 and Table 5 suggests that *on average* countries with low emission per capita rates in 1950 experienced higher growth rates over the period 1950 to 2000 than countries with relatively high emission per capita levels in 1950.

The important question to consider is then: how does this result compare with the distributional analysis presented in Section 1 and what are the implications for projection models?

The existence of beta convergence suggests that there is some intra-distributional mobility in emissions per capita. Keeping in mind that the regression results are an indication of *average* behaviour, this result is entirely consistent with Figure 7. The contour plots in Figure 7 suggest that whilst there is persistence at emissions per capita levels below around 6 times the cross country mean, countries with emissions per capita above this level do tend to converge. These countries are generally OECD countries that are more likely to share similar

[3] Recently, beta convergence has been analysed using panel data techniques. Estimation techniques such as fixed effects allow unobservable factors to be controlled for. In this report, the regression analysis is included to demonstrate the correlation between the level of emissions and the growth rate in emissions and the simple cross-sectional regression analysis is sufficient to demonstrate this point. A panel data analysis of emissions per capita is likely to be subject to serial correlation and other complicated dynamics that require an in depth analysis beyond the scope of this report.

characteristics.[4] Figure 43 and Table 5 highlight the strong tendency towards beta convergence in OECD countries. For OECD countries, therefore, there is evidence of beta convergence and weak evidence of distributional or sigma convergence.

For the majority of countries, however, Figure 7 suggests that there is persistence rather than convergence. When OECD countries are excluded from the scatter plot in Figure 43 (consider only the grey points), the evidence in favour of beta convergence appears very weak (the statistical significance of beta convergence in non-OECD countries is small and not robust to alternative sample definitions). In addition, many of the countries have very low levels of emissions per capita in 1950 (see Figure 3) and small (levels) increases in emissions per capita are measured as large growth rates. Figure 43 therefore suggests (very) weak beta convergence for non-OECD countries even though the distributional analysis in Section 1 demonstrated that the dispersion of the data set is not decreasing and that mobility in this area of the distribution is small. These results are not inconsistent. They demonstrate a point highlighted in Section 1. Convergence analyses are affected by the definition of convergence assumed by the researcher. Sigma convergence is a much stronger condition than beta convergence. Both sigma and beta convergence analyses can be affected by data characteristics and transformations. They are also affected by the sample definition. The evidence in favour of convergence in emission per capita rates for OECD countries suggests that emissions per capita may exhibit a tendency towards *conditional* convergence. There is little evidence of *unconditional* convergence. With respect to projection models, this result could be interpreted in a number of ways.

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[4] The sample (Sample A) used to generate the plots in Figure 7 does not include OPEC countries and countries with relatively high emission per capita rates are generally OECD countries. The sample used to estimate Equation 5 does include OPEC countries. This difference is deliberate. In the analysis of Section One, the inclusion of OPEC countries obscures the dominant features of the overall data set and the interpretation of graphs. This is not the case in the regression analysis of this section. These sample differences do not affect the overall results in this report or the conclusions drawn from them.

Firstly, there is no evidence of unconditional convergence in emissions per capita and projection models that assume absolute convergence in emissions per capita are not reflective of the empirical evidence. The existence of convergence within the OECD region (*conditional* convergence) suggests that convergence assumptions may be useful in limited circumstances. If the projection exercise is restricted to a sample of countries characterised by similar economies then emission per capita convergence assumptions may be useful. Researchers should be aware, however, that emission per capita levels are unlikely to converge in an absolute sense, even within the OECD region. Differences in natural endowments are likely to lead to persistent differences in the emissions intensity of energy use, even if income per capita and other key energy variables (as identified in Section 3) converge. As described in Section 2, whilst GDP per capita and energy supplied per unit of GDP in the OECD region show some tendency towards convergence, the emissions intensity of energy supplied does not. Section 4 described how this variable is related to fossil fuel endowments.

6. *Conclusions*

This report examines the empirical evidence for convergence in a range of economic variables but with a focus on carbon emissions per capita. This is important both as a basis for undertaking projections of future emissions and because there are policy proposals currently being debated which wish to impose this onto the global economy. The approach to convergence analysis in this paper is statistical and focuses on the key characteristics of the *distribution* of emissions per capita. There is little evidence that cross country emission per capita rates are converging. To examine this result in more detail, the IPAT identity was used to disaggregate emissions and examine trends in key macroeconomic variables. When a large cross section of countries is considered, there is little evidence of convergence in GDP per capita, the energy intensity of output or the emissions intensity of energy supplied. If the analysis is restricted to the OECD region, there is some evidence of convergence in GDP per capita and the energy intensity of output. These trends lead to a weak tendency for emissions per capita in the OECD to converge. There is, however, no evidence that the emissions intensity of energy supplied is converging and cross country differences in emissions per capita are likely to persist due to differences in natural endowments.

Projection models that assume absolute convergence in emissions per capita are not reflective of the empirical evidence. Projection models that include assumptions about emission per capita convergence, or energy intensity convergence, must define convergence conditionally, either through sample selection or additional assumptions on key macroeconomic variables. Conditional convergence is a controversial concept. It is not clear how this data feature should be interpreted. In the growth literature, conditional beta convergence predicts that *if countries are similar with respect to preferences and technology* then there is a tendency towards convergence in levels of per capita product and income. The usefulness of this result when generating long run projections depends on how likely it is that countries will also converge in terms of preferences and technology (steady state characteristics) as well as endowments.

Conditional convergence analyses are useful in demonstrating factors that lead to persistent differences in the variable of interest. The distinction between conditional and unconditional convergence would not exist if these control factors also converged. Empirical evidence that unconditional convergence is not a feature of the data but conditional convergence is suggests that these control factors are, in fact, not converging across countries. This result may be due to data limitations, given convergence is likely to be a slow process that occurs over many decades. If a strong argument for the eventual convergence of control factors can be made, then there may be some support for the use of conditional convergence assumptions in long run projections. The empirical evidence in this report, however, suggests that there is no tendency towards convergence in emissions per capita when a large cross section of countries is considered. If the analysis is restricted to the OECD, there is some tendency towards convergence, but absolute convergence is unlikely to result because of differences in fossil fuel endowments. Even within the OECD region, therefore, although convergence assumptions may help to generate trends in emissions over long time periods, absolute convergence is not consistent with the empirical data. Given the lack of empirical support for historical convergence in emissions per capita, the results of projection models that assume convergence in emissions per capita (or in energy intensities) likely reflect wishful thinking rather than empirical observations and should be interpreted with caution.

Appendix

Summary Statistics

Section 1 considers six summary measures of dispersion: 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 variance of a data set is defined as

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

where $\overline{Y}$ 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 standard deviation of a data set is defined as

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

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

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

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

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

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

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

The median absolute deviation is defined as

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

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.

<u>Density Estimates</u>

The kernel-smoothed estimates of the cross-country density of fossil fuel CO_2 emissions were obtained using the Kernel Estimator described in Pagan and Ullah (1999, p 9).

The estimator is defined as

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

where x_i is the data under consideration

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

the window width, h = 0.9*min(σ, (R/1.34))$n^{-1/5}$, where R is the interquartile range; and

n is the sample size.

The stochastic kernel detailed in Quah (1995) is used to estimate the intra-distribution dynamics. The calculation of the stochastic kernel estimates is similar to the calculation of a non parametric conditional density function:

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

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 described above), the denominator is derived 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.

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

Samples

Table A1: Sample A and Sample B

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.

OPEC countries are excluded from the analysis in this section. 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.

This data is sourced from CDIAC (2004). See Marland et. al. (2003).

Section 3 Data Sample

Albania
Angola
Argentina
Australia
Austria
Bahrain
Bangladesh
Belgium
Benin
Bolivia
Brazil
Brunei
Bulgaria
Cameroon
Canada
Chile
China
Colombia
Congo
Costa
Cote
Cuba
Cyprus
Czech
Denmark
Dominican
Ecuador
Egypt
El Salvador
Ethiopia
Finland
France
Gabon
Germany
Ghana
Gibraltar
Greece
Guatemala
Haiti
Honduras
Hong
Hungary
Iceland
India
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kenya
Korea
Lebanon
Luxembourg
Malaysia
Malta
Mexico
Morocco
Mozambique
Myanmar
Nepal
Netherlands
Nicaragua
North Korea
Norway
Oman
Pakistan
Panama
Paraguay
Peru
Philippines
Poland
Portugal
Romania
Senegal
Singapore
Slovak
South Africa
Spain
Sri Lanka
Sudan
Sweden
Switzerland
Syria
Taipei
Tanzania
Thailand
Togo
Trinidad
Tunisia
Turkey
United Kingdom
United States
Uruguay
USSR
Vietnam
Yemen
Yugoslavia
Zambia
Zealand
Zimbabwe

Section 4 Data Sample

Albania
Algeria
Angola
Argentina
Australia
Austria
Bahrain
Belgium
Bolivia
Brazil
Bulgaria
Canada
Cape Verde
Chile
China
Colombia
Costa Rica
Cuba
Denmark
Djibouti
Dominican Republic
Ecuador
Egypt
El Salvador
Equatorial Guinea
Finland
France
Gambia
Germany
Ghana
Greece
Guatemala
Haiti
Honduras
Hong Kong
Hungary
India
Indonesia
Iraq
Ireland
Israel
Italy
Jamaica
Japan
Jordan
Kenya
Lebanon
Liberia
Libya
Madagascar
Mauritius
Mexico
Mongolia
Morocco
Mozambique
Netherlands
New Zealand
Nicaragua
Nigeria
North Korea
Norway
Panama
Paraguay
Peru
Philippines
Poland
Portugal
Puerto Rico
Qatar
Reunion
Romania
Sierra Leone
South Africa
South Korea
Spain
Sri Lanka
Sudan
Sweden
Switzerland
Syria
Taiwan
Thailand
Trinidad and Tobago
Tunisia
Turkey
Uganda
United Kingdom
United States
Uruguay
Venezuela
Zaire

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