Co-fluctuation patterns of per capita carbon dioxide emissions: The role of energy markets

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Abstract

This paper applies principal component analysis to investigate the linkages, or dominant co-fluctuation patterns, of per capita carbon dioxide emissions across countries for the time period 1950-2000. Energy resource world markets are investigated as an offsetting mechanism possibly coordinating emission fluctuations between countries. The results of the analysis provide evidence that world energy resource markets are acting as a coordinating mechanism for emission fluctuations in most cases. The results also suggest that until recently the dominant emission co-fluctuation pattern for developed countries differs from the dominant emission co-fluctuation pattern for developing countries. The common fluctuation pattern found in the 1984-2000 time period suggests that an offsetting mechanism does exist and will help contain global per capita emissions into the future. The strong degree that emissions are linked between countries and energy markets acting as an offsetting mechanism suggest that to be successful a global agreement to address climate change must require emission reductions by all major emitters, not just the developed countries.

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1. Introduction

There has been a significant amount of research into the statistical characteristics of national per capita carbon dioxide (CO2) emissions. This topic is important for projecting future global emissions and forecasting changes in the distribution among countries. Many studies have focused on tests of convergence of national per capita CO2 emissions (e.g., Aldy, 2006; Nguyen Van, 2005; Ordas Criado and Grether, 2011; Strazicich and List, 2003). Stationarity at the global and/or national level has been examined by McKitrick et al., (in press) and Romero-Avila (2008). A key question at present is the extent to which emissions growth in one country or region affects emissions elsewhere. McKitrick et al., (in press) find evidence that offsetting effects occur between countries, and may constrain global per capita emissions in the future. The purpose of this paper is to investigate more closely the extent to which national per capita CO2 emissions are linked across countries, and whether those linkages can be explained based on energy markets, openness to trade, and other factors.

This paper applies principal component analysis (PCA) to investigate the co-fluctuation patterns of per capita carbon dioxide emissions across countries. PCA allows for extraction of ranked orthogonal vectors from a data matrix, where ranking is by the percentage of underlying explained variance. If all countries' emissions respond linearly to the same external shocks, the first principal component (PC1) will explain a high proportion of variance in the whole data set. If countries' emissions are independent of each other over time, the first principal component will explain relatively little of the underlying variance. Hence we interpret the explained variance associated with the first principal component as an index of homogeneity of national per capita CO2 emissions.

Our hypothesis is that energy prices transmit information across borders in such a way as to increase coordination of emission fluctuations. This is tested by examining the effect of energy prices on the index of homogeneity. We find evidence in support of the hypothesis; however, the pattern of emission fluctuations differs between developing and developed countries until the most recent time period (1984-2000). We then examine the effects of openness to trade and government intervention, and find that neither of these factors have an identifiable coordinating effect on emission fluctuations between countries. Overall the evidence suggests that emissions are strongly linked between countries, and we discuss what this may imply about future emission growth and global agreements to address climate change.

The next section discusses the statistical characteristics of per capita CO2 emissions. Section 3.1 introduces the data, the analytical methodology, and analyzes a global sample, a developed country sample, and a developing country sample. Section 3.2 applies the methodology to samples of countries defined by region. Section 3.3 investigates the importance of openness to trade and government size. Section 4 concludes the paper.

2. Background

There are several different motivations for examining the historical statistical characteristics of national per capita carbon dioxide emissions. One is that numerous studies projecting future climate change assume growth in per capita CO2 emissions under assumptions that differ from what has been observed historically. For example, the Special Report on Emission Scenarios (SRES) produced by the Intergovernmental Panel on Climate Change (IPCC, 2000) includes projections of emissions using models that inherently assume absolute convergence in per capita emissions. But convergence has not been established in the historical data despite numerous attempts to test for it (Aldy, 2006; McKibben and Stegman, 2005; Nguyen Van, 2005; Ordas Criado and Grether, 2011; Stegman, 2005; Strazicich and List, 2003). The studies investigating convergence in per capita CO2 emissions use empirical techniques developed in the macroeconomic literature on income convergence (such as Barro and Sala-i-Martin, 1992; Carlino and Mills, 1993; Quah, 1996). Some of the research discussed in this section compares statistical properties of data used for climate change projections with those of historical data. As pointed out by Aldy (2006), whether or not there is a historical basis for projections of per capita emissions is very important for informing policy makers who are considering different proposals for, e.g., the distribution of emission entitlements in any global framework addressing climate change.

Ordas Criado and Grether (2011) provide the most comprehensive analysis out of the convergence studies. They apply non-parametric dynamic distributional analysis and find that between 1960 and 2002 national per capita CO2 emissions have actually diverged globally and predict that emissions will continue to diverge into the future. This result is certainly at odds with the SRES scenarios. However, they do find evidence that the per capita emissions of developed countries have converged conditional on macroeconomic variables.

Another motivation for investigation of the historical statistical characteristics of national per capita emissions is that there is a theoretical basis in environmental economics to expect emission convergence. The environmental Kuznets curve (EKC) hypothesis suggests that the relationship between national income and emissions follows an inverse 'u-shape' (Andreoni and Levinson, 2001; Grossman and Krueger, 1991, 1995; Lopez, 1994). The EKC hypothesis implies that emissions will converge as incomes converge. This can be incorporated into theoretical "green" growth models (e.g., Brock and Taylor, 2010) to predict conditional emission convergence associated with convergence in national income. Ordas Criado and Grether (2011) find evidence of conditional convergence amongst developed countries, but not when all countries are considered.

Another historical feature of interest of per capita CO2 emissions is the trend in the global average. McKitrick et al., (in press) find that world per capita emissions are stationary around a stable mean and have remained so for the past three decades. They then use this result to assign probabilities to the emission predictions of the IPCC SRES. They conclude that 33 of the 40 scenarios can be rejected, and the 7 scenarios that remain are all on the lower-end of emissions of the IPCC scenarios. They also find that emissions in 95 of 121 countries were stationary[2]. Since the emissions of 26 countries are found to be non-stationary while the global mean is stationary, emissions appear to be cointegrated. McKitrick et al., (in press) suggest this may be due to equilibrating effects of world energy markets (i.e., changes in emissions of the 26 countries systematically offset each other). If such an equilibrating mechanism exists, it may restrict or prevent an upward trend in global per capita carbon dioxide emissions in the future.

If integration with world energy markets leads to the cointegration of emissions among countries, then energy prices should help explain co-movements of per capita CO2 emissions between countries. If emissions are assumed to be positively correlated with energy consumption, increased emissions in one country should impact the world prices for energy resources positively, inducing reduced emissions in other countries. The more highly integrated a country is with world energy markets, the more responsive their emissions will be to pressure on prices. It is also conceivable that large income effects could cause the emissions of some countries (those with large endowments of energy resources) to increase in response to increasing world prices. If all countries are assumed to have similar levels of integration with energy resource world markets, then we would expect to see systematic responses to energy price changes, including pairwise off-setting of per capita emission fluctuations.

In the subsequent section we empirically investigate the co-fluctuation patterns of per capita CO2 emissions across countries, in particular looking at world energy prices as a coordinating mechanism for emission changes across countries. We then add in other indicators of openness to markets to examine the effect they play in coordinating emission variations.

3. Data, Methodology, and Analysis

3.1. Data, Methodology, and Analysis: Global, OECD, and non-OECD Samples

The analysis in this paper uses annual per capita emissions data[3] over the interval 1950 to 2000 for 132 individual countries[4]. The emissions data are measured in metric tonnes of carbon per capita produced from fossil fuel burning, gas flaring, and cement manufacturing. The emissions data were obtained from the Carbon Dioxide Information and Analysis Center (Marland et al., 2003). Seven countries with per capita emissions greater than 15 tonnes, in any year, were removed as outliers. Descriptive statistics for the emissions of the 132 countries used in the sample for the year 2000 are presented in Table 1. The per capita emissions of OECD countries are, on average, 2.5 times larger than those of non-OECD countries. The dispersion (standard deviation) of the per capita

[2]Some of the 95 countries had emissions that were stationary around a stable mean. And some of the 95 countries had emissions that were trend stationary.

[3]See Appendix A for further information concerning all data used in this paper.

[4]A list of countries included can be found in Appendix B.

emissions of developed countries is lower than that of the per capita emissions of developing countries.

Prices for crude oil, natural gas, and coal were obtained from the Annual Energy Review produced by the Energy Information Administration (EIA) for the interval 1950 to 2000. The prices for crude oil are the average annual crude oil domestic first purchase prices for the United States (nominal USD per barrel). The natural gas prices are the average annual US natural gas wellhead prices (nominal USD per thousand cubic feet). The coal prices are the average annual US free-on-board prices of coal at the point of first sale (nominal USD per short ton). These nominal prices were converted into real prices using consumer price index (CPI) data from the US Department of Labor, Bureau of Labor Statistics. Applying the test proposed by Kwiatkowski, et al. (1992), we fail to reject the null hypothesis of stationarity for all three price series at the 5% significance level. Furthermore, conducting the test proposed by Elliott, et al. (1996), we reject the null hypothesis of a unit root in all three price series at the 1% significance level. The test statistics for both tests are reported in Appendix B.

The methodology begins by applying principal component analysis (PCA) to identify the dominant fluctuation patterns in the emission data. PCA has been widely used in many fields. In economics it has been applied, for example, in dynamic factor models for forecasting macroeconomic variables (Stock and Watson, 2002) and for examining business cycles (Forni and Reichlin, 1998). It has also been used to correct for cross-sectional dependence when testing for unit roots in panel data analysis (Bai and Ng, 2004). PCA has also been used recently to analyze fluctuation patterns of unemployment across OECD countries (Smith and Zoega, 2007). The following presentation of PCA loosely follows Johnson and Wichern (2007). To obtain the most dominant pattern in the data, PCA summarizes a centered emissions data matrix C for K countries over T periods

$$C = \begin{pmatrix} c_{11} & \cdots & \cdots & c_{1N} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ c_{T1} & \cdots & \cdots & c_{TN} \end{pmatrix}$$

by finding a matrix $z_1 a_1^T$ of rank one, where z_1 is a Tx1 vector and a_1 is a Kx1 vector of scaling coefficients. This is done by minimizing the trace of the sum of squares of the discrepancy matrix, $(C - z_1 a_1^T)$ with respect to z_1

$$\min_{z_1} tr\left((C - z_1 a_1^T)^T (C - z_1 a_1^T)\right) \tag{1}$$

$$\text{subject to } \; a_1^T a_1 = 1, \tag{2}$$

where the normalization (2) is necessary to ensure a unique solution. With some linear algebra, equation (1) can be re-written as

$$\min_{z_1} tr(C^T C) - 2 z_1^T C a_1 + z_1^T z_1. \tag{3}$$

The derivative of equation (3) with respect to z_1 yields

$$-2Ca_1 + 2z_1 = 0,$$

$$\Rightarrow z_1 = Ca_1. \tag{4}$$

Equation (4) shows z_1 as a function of a_1. Combining equations (3) and (4) yields

$$\min_{a_1} tr(C^T C) - a_1^T C^T C a_1 \tag{5}$$

subject to equation (2).

The minimization problem outlined in equation (5) is equivalent to the following maximization problem

$$\max_{a_1} a_1^T C^T C a_1 \tag{6}$$

subject to equation (2).

The optimality condition for the maximization problem outlined in equation (6) is

$$(C^T C - \mu_1 I)a_1 = 0, \tag{7}$$

where μ_1 is the Lagrange multiplier and I is an identity matrix. From equation (7) it is clear that μ_1 is also the largest eigenvalue of $C^T C$, and a_1 is the eigenvector of $C^T C$ that corresponds to the largest eigenvalue. Since z_1 is associated with the largest eigenvalue, it is considered the first principal component (PC1) of the matrix C. Furthermore, since μ_1 is a scalar, equation (7) can be solved for μ_1

$$\mu_1 = a_1^T C^T C a_1. \tag{8}$$

Substituting equation (4) into equation (8) produces μ_1 as a function of z_1

$$\mu_1 = z_1^T z_1. \tag{9}$$

Equation (9) can be used to obtain the variance of z_1

$$\mathrm{var}(z_1) = \frac{z_1^T z_1}{T} = \frac{\mu_1}{T}. \tag{10}$$

Johnson and Wichern (2007) demonstrate that the variance of the matrix C is a function of the sum of the eigenvalues of $C^T C$

$$\mathrm{var}(C) = tr(\Sigma) = \frac{tr(C^T C)}{T} = \frac{\sum_{i=1}^{K} z_i^T z_i}{T} = \frac{\sum_{i=1}^{K} \mu_i}{T}, \tag{11}$$

where Σ is the covariance matrix of C. From equation (10) and equation (11) it is possible to calculate the proportion of the variance of C that is explained by z_1

$$\lambda(C) = \frac{\text{var}(z_1)}{\text{var}(C)} = \frac{\mu_1}{\sum_{i=1}^{K} \mu_i} = \frac{\mu_1}{\mu_1 + \mu_2 + \ldots + \mu_K}. \tag{12}$$

PC1 (z_1) explains the largest proportion of variation in the data since $\mu_1 > \mu_2 > \ldots > \mu_K$.

For computational efficiency, we use the singular value decomposition method to derive the principal components as recommended by Joliffe (1986). We also scale the columns of C by their respective standard deviations, yielding a $C^T C$ matrix that is a correlation matrix rather than a covariance matrix. Using PCA based on the correlation matrix makes it easier to compare the PCA results from two different data matrices. Using the correlation matrix is also favoured if the columns of the data matrix highly differ in variance (which is the case here, especially amongst the emissions data for the developing countries). The major disadvantage of using the correlation matrix instead of the covariance matrix is that the PCA coefficients, the elements of a_1, are more difficult to use for statistical inference, however, my analysis does not rely on the distribution of the PCA coefficients. As mentioned by Joliffe (1986), PCA is not appropriate for analyzing strongly co-trending data. However, this may not be a problem in this paper since McKitrick et al., (in press) showed that global per capita CO2 emissions are stationary with no trend, suggesting that the emissions of all countries cannot be co-trending. Out of the 121 country sample studied by McKitrick et al., (in press), only the emissions of 45 countries followed trends with positive heterogeneous trend coefficients. Also, only the emissions of 3 countries studied did not have heterogeneous structural breaks. The results of McKitick et al., (in press) suggest that we can assume that co-trending is not pervasive in the data and that PCA is applicable. If this assumption is incorrect, then PC1 may be a common trend rather than a common fluctuation pattern.

PC1 (z_1) is the factor that represents the optimal linear summary of the co-fluctuation of per capita emissions across the K countries. In this sense, PC1 is often referred to as the dominant common factor. The signs of the elements of a_1, the PCA coefficients or factor loadings, indicate which countries emissions are co-moving and which countries emissions are off-setting. Figure 1 provides an example of co-fluctuation: The hypothetical data in this example consist of five time series that differ in levels, but follow the same fluctuations. The common fluctuation was drawn from a normal distribution with zero mean and standard deviation of 0.29. Three of the series were generated with the common fluctuation series added to their levels (perfect co-movement). The other two series have the common fluctuation series subtracted from their levels, to mimic offsetting. PCA conducted on this data set produces a PC1 that explains 100% of the variation between the series. The signs of the PCA coefficients for the three series that experience co-movement are positive, and the signs of the PCA coefficients for the two series that are co-moving in the opposite direction are negative. Therefore, the proportion of total variation explained by PC1 is a measure of the degree to which the columns of the data matrix are co-moving in absolute value over the time period.

Figure 2 provides an example of series that move independently of each other. The series were all generated using different random fluctuation series drawn from a normal distribution with zero mean and standard deviation of 0.29, hence each series follows a different random fluctuation pattern. PCA in this case produces a PC1 that explains only 32.7% of the variation between series. The results from the two examples suggest that the proportion of total variation explained by PC1 can be thought of as an index of the homogeneity of emission fluctuations across countries. Throughout this paper, the index of homogeneity of emissions will be denoted by $\lambda(X)$, where X is the data matrix in question (see equation (12)).

It is important to point out that PCA cannot measure the convergence of emissions, just the coherence of emission fluctuations across countries. This is because the data are centered when applying PCA, i.e., levels no longer matter. Figure 3 provides an example of sigma convergence, a reduction in dispersion between series overtime, with a low level of homogeneity of fluctuations, $\lambda =$ 35%. Each series in Figure 3 was generated, as in Figure 2, with a different set of random fluctuations. To create sigma convergence, the outer series were constructed to trend toward the middle series. Figure 4 provides an example of sigma convergence with a high level of homogeneity of fluctuations, $\lambda = 80\%$. The series in Figure 4 were generated, as in Figure 1, following the same set of random fluctuations. Once again, the outer series were constructed to trend toward the middle series. The purpose of this paper is to focus on whether emission co-fluctuation between countries is driven by a common factor (e.g., energy prices), not whether emissions are converging; and it is in this focus on co-fluctuations that PCA is deemed appropriate.

We first calculate $\lambda(C)$ for per capita emissions for a global sample of 132 countries over intervals of 17 years (1950-1966, 1967-1983, 1984-2000). Figure 5 shows scree-plots of the proportion of variance explained by each principal component of the PCA conducted on the global sample. The height of the first column represents $\lambda(C)$. The numerical values of $\lambda(C)$ are shown in Table 2. $\lambda(C)$ follows a u-shape over time for the global sample. Homogeneity is highest in the early time period, and lowest in the middle time period. $\lambda(C)$ is relatively high (> 0.5) for all three time periods suggesting that globally, per capita emissions are strongly linked across countries.

PCA is also applied on a sample of developed countries (the 28 OECD countries as of the year 2000) and a sample of developing countries (the 104 non-OECD countries as of the year 2000). Figures 6 and 7 show scree-plots of the proportion of variance explained by each principal component of the PCA conducted on the emissions of the developed countries and the emissions of the developing countries respectively. The values of $\lambda(C)$ are displayed in Table 2. $\lambda(C)$ for the developed countries decreases from 0.844 to 0.691 over the three time periods. $\lambda(C)$ for the developing countries increases from 0.619 to 0.689 over the three time periods. Considering the global sample results in association with the developed and developing results, the pattern of emission fluctuation differs between developed and developing countries in the first two time periods. For the 1984-2000 time period, $\lambda(C)$ is equal between the developed and developing countries (0.69 after rounding). The difference between this value and the global value is small, 0.02, suggesting coherence of emission fluctuation patterns between developed and developing countries in the later time period. This result is in contrast to the results of the convergence studies discussed in section 2. Our results show the emissions of developed and developing countries acting similarly in recent history, whereas, the convergence studies generally have them acting differently (i.e., conditional emissions convergence amongst developed countries, but not amongst developing countries). The emissions of developed and developing countries following the same pattern of fluctuation and being strongly linked is a result in support of global per capita emissions remaining stationary around a stable mean into the future. This result supports the predictions of McKitrick et al., (in press), and makes convergence in per capita emissions less relevant (i.e., convergence is not as important if there is a global offsetting mechanism).

The methodology now turns to investigating the coordinating role of energy prices (i.e., trying to identify international energy markets as the offsetting mechanism). Each country's emissions, $c^j_{i,t}$, are regressed on world prices of coal (cp_t), natural gas (ngp_t), and oil (op_t)

$$c^j_{i,t} = \beta_0 + \beta_1 cp_t + \beta_2 ngp_t + \beta_3 op_t + u^j_{i,t},\ i = 1, \ldots K,\ t = 1, \ldots, T, \qquad (13)$$

where j refers to the interval: early (1950-1966), middle (1967-1983), or late (1984-2000). The residuals from these regressions represent the portion of per capita emissions in each country not explained by prices. The residuals are assembled into a TxK matrix, U^j

$$U^j = \begin{pmatrix} u^j_{1,1} & \cdots & \cdots & u^j_{1,K} \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ u^j_{K,1} & \cdots & \cdots & u^j_{K,K} \end{pmatrix}.$$

PCA is then undertaken on U^j and PC1 is obtained,[5] i.e., the index of homogeneity, $\lambda(U^j)$, once the effect of prices is removed. If energy prices have an effect on emissions then it is expected that energy prices are contributing to

[5] The Kwiatkowski, et al. (1992) test suggests the residuals of each individual regression are stationary. However, the Elliot, et al. (1996) test suggests that some of the residuals may have a unit root; although, unit root tests suffer from low power in small samples (Cochrane (1991)). We do not expect this to be an issue for the PCA method since PCA is regularly applied to nonstationary data to correct for cross-sectional dependence when testing for unit roots in panel data, e.g., Bai and Ng (2004), Moon and Perron (2004), etc.

one of the principal components and $\lambda(U^j) \neq \lambda(C^j)$. If energy prices are contributing to the dominant common factor (PC1) suggesting that energy markets have a coordinating effect on emissions, then it is expected that $\lambda(U^j) < \lambda(C^j)$. If energy prices are not contributing to PC1, but are contributing to lower principal components, then it is expected that $\lambda(U^j) > \lambda(C^j)$ because $\lambda(C^j)$ and $\lambda(U^j)$ are calculated using the cumulative percentage of total variance as the denominator (see equation (12)). Energy prices influencing lower principal components suggests that energy prices are not having a coordinating effect on emissions over the whole sample. Table 2 reports the difference and the percent change between $\lambda(C^j)$ and $\lambda(U^j)$

$$\Delta H^j = \lambda(U^j) - \lambda(C^j), \tag{14}$$

$$\%\Delta H^j = \frac{\lambda(U^j) - \lambda(C^j)}{\lambda(C^j)}. \tag{15}$$

To assess the significance of the changes, it is necessary to estimate confidence intervals for ΔH^j and $\%\Delta H^j$ through bootstrap simulations[6]. The bootstrap simulations consist of generating multiple bootstrap samples from the emissions matrix, holding the cross-sectional dimension constant to preserve the correlation structure between countries, and then calculating ΔH^{*j} and $\%\Delta H^{*j}$ from the bootstrap samples[7]. This process is repeated 999 times for each interval, for each sample of countries. Critical values[8] are calculated for ΔH^j and $\%\Delta H^j$.

If ΔH^j and $\%\Delta H^j$ are negative and significant, then the portion of emission data unexplained by prices exhibits less coherence than the original emissions data, suggesting energy resource prices are contributing to the dominant common factor (PC1). If ΔH^j and $\%\Delta H^j$ are positive and significant, then the portion of emission data unexplained by prices exhibits more coherence than the original emissions data, suggesting energy prices do not influence the dominant common factor (PC1). However, it also suggests that the dominant common factor now explains a larger percentage of the variance, suggesting that energy prices influence a lower order common factor (e.g., PC2, PC3, etc.). In this situation, energy resource prices are not having an overall coordinating effect on the emissions of countries in the sample. Prices may still be having a coordinating effect on the emissions of a sub set of countries in the sample, but this minor coordinating effect has a negative effect on the emission linkages of all countries in the sample.

The ΔH^j and $\%\Delta H^j$ values for the global, developed, and developing samples are displayed in Table 2. For the global sample, the values of ΔH^j and

[6]Further description and explanation of the bootstrap simulations is presented in Appendix C.

[7]This bootstrap approach is applicable under the assumption that emissions are independent and identically distributed in the time-series dimension. If this assumption is violated, then application of the Block bootstrap (see MacKinnon (2002)) would result in more appropriate confidence intervals.

[8]Appendix C, Tables C.8, C.9, C.10, C.11 and C.12.

$\%\Delta H^j$ are large, negative, and statistically significant at the 1% level for the early and late time periods. Therefore, there is evidence to suggest that energy resource prices were contributing to the dominant common factor in the early and late time periods and that energy resource markets were acting as a coordinating mechanism for emissions between countries at the global level. In the middle period, the global results have positive values and are statistically significant at the 10% level. This result suggests that between 1967 and 1983 something other than energy prices was influencing the dominant common factor, and that energy prices were affecting a lower principal component. This result suggests that in this time period, energy prices were not globally coordinating emissions between countries.

For the developed countries, the values of ΔH^j and $\%\Delta H^j$ are negative and significant in all three time periods. Therefore, the developed country results are as expected: energy prices have been a key mechanism coordinating emission fluctuations across developed countries.

The values of ΔH^j and $\%\Delta H^j$ for the developing countries are negative and significant at the 1% level for the late period. The values of ΔH^j and $\%\Delta H^j$ are not statistically significant in the early and middle time periods, suggesting that energy prices did not coordinate emissions in these time period. This could possibly be due to developing countries pursuing policies to shield their economies from world energy resource prices during these periods.

The result that the emissions of both the developed countries and developing countries are mainly coordinated in the 1984-2000 period by energy markets lends support to the global emissions predictions of McKitrick et al., (in press). Also, the strong degree of emissions co-fluctuation combined with energy resource markets as an offsetting mechanism suggests that any global agreement to address climate change requires emissions reduction efforts by all major emitters to be successful. For example, if an agreement only requires emissions reductions by developed countries, as the Kyoto Protocol did, then these reductions and the associated reduced use of energy resources in developed countries will result in increased energy use and corresponding increased emissions in developing countries.However, the absence of energy markets playing a coordinating role on the emissions of developing countries in the early and the middle time periods suggests that other factors need to be considered.

3.2. Regional Analysis

To obtain more insight into the coordinating role of energy prices, countries were further divided into 7 regional groups: North America, Europe (excluding former communist countries), former communist European countries, Africa, Middle-East, Central & South America, and Asia & Oceania (subscripts are, respectively, *na, we, ee, af, me, sa, ao*).

The numerical results for the regional groups are listed in Table 3. The index of homogeneity of emission fluctuations for North America ($\lambda(C_{na})$) follows a u-shape over time; $\lambda(C_{na})$ experiences a large decrease in the 1967-1983 period, but returns to the 1950-1966 level in the 1984-2000 period. The Asia & Oceania region is also characterized by a u-shape in $\lambda(C_{ao})$ over time. The homogeneity of emission fluctuations for Western Europe ($\lambda(C_{we})$) is decreasing over all time periods. The homogeneity of emission fluctuations for Africa ($\lambda(C_{af})$), the Middle-East ($\lambda(C_{me})$), and Central & South America ($\lambda(C_{sa})$) follow inverse u-shapes over time. The former Eastern Bloc countries have extremely high levels of homogeneity of emission fluctuations ($\lambda(C_{ee})$) over all three time periods.

Looking at the $\%\Delta H$ column in Table 3, North America and Central & South America appear to have similar patterns. These two regions are characterized by large, negative, and statistically significant values of $\%\Delta H$ in 1950-1966, followed by positive and statistically significant values of $\%\Delta H$ in 1967-1983, followed by negative and statistically significant values of $\%\Delta H$ in 1984-2000. This suggests that prices were having an impact on emission co-fluctuation in the first and last time periods, but not in the middle time period. In the middle period, energy prices are having a detrimental effect on the overall level of emission linkages in these regions. This could be due to a large percentage of countries implementing domestic policies in response to the OPEC oil shocks (e.g., the National Energy Program in Canada that consisted of price ceilings on petroleum and partial nationalization of the Canadian petroleum industry). Considering the results from the previous section, it is surprising that these two regions have similar $\%\Delta H$ patterns as a developed region. This could be due to the fact that these are neighbouring regions.

Values of $\%\Delta H$ for Western Europe are large, negative, and statistically significant at the 1% level for all three time periods. The former Eastern Bloc countries also experience negative, statistically significant values of $\%\Delta H$ in all time periods. Again, a developing region follows the same $\%\Delta H$ pattern as a developed region in close proximity. Also, it is very interesting that world prices had an effect on these planned economies. This could possibly be due to the commencement of oil sales on the world market by the USSR in the 1970s, rather than trading oil in greater quantities to the Eastern Bloc countries (Stent (1982), Gustafson (1989)).

For the Middle-East, $\%\Delta H$ is negative and statistically significant in the middle and late periods, suggesting prices were having a positive influence on emission co-fluctuation in these periods. $\%\Delta H$ is positive and significant in the early period, suggesting that energy prices were not always a coordinating effect on emissions in this region. For Africa, energy prices are having a coordinating effect on emissions in the early and late periods. However, ΔH and $\%\Delta H$ are not statistically significant for the middle time period, suggesting that energy prices were not influencing a common factor at all. This could be the result of governments enacting policies aimed at protecting their economies from the OPEC oil shocks. The results for Asia and Oceania suggest that energy prices were influencing a common factor, but not influencing the dominant common factor in the first two time periods. However, the Asia and Oceania results also suggest that energy prices were affecting the dominant common factor in the 1984-2000 time period.

The results from the multiple applications of principal component analysis are consistent with the view that world energy prices have increased the homogeneity of emission fluctuations across most countries for the early and late time periods. However, for Africa in the second time period, prices are not having a coordinating effect on emissions. For many regions, energy prices are not always having a coordinating effect on emissions, especially in the middle time period. The absence of price effects as the strongest coordinating mechanism could be attributed to countries (developed and developing) following policies that shield their markets from world energy prices. The results for the 1984-2000 time period show energy prices having a significant coordinating effect in all regional groups. If domestic price shielding policies were responsible for the absence of price effects, then such policies must have been weakened or discontinued in most countries. The next section will expand the analysis in an effort to identify other factors that may contribute to the homogeneity of emission fluctuations.

3.3. Expanded Analysis to Consider Trade and Government Intervention

The analysis in this section will be similar to that in the preceding sections, but will investigate two additional factors that may contribute to homogeneity of emission fluctuations across countries. It is conceivable that freer trade could provide the impetus behind emission co-fluctuations between countries. Antweiler, Copeland, and Taylor (2001) decompose the relationship between freer trade and emissions into three effects: scale (change in emissions due to trade induced changes in the amount of output), technique (change in emissions due to trade induced changes in production methods), and composition (change in emissions due to trade induced changes in the composition of output). If two countries have increased trade with each other, the cumulative effect on emissions could conceivably be increased emissions in both countries, decreased emissions in both countries, or increased emissions in one country and decreased emissions in the other. In this sense, the emissions of the two countries are linked through trade. Countries that are highly open to international trade would be expected to have emissions that are more linked, than countries that have low levels of openness to trade. Therefore, it is expected that emissions amongst countries with high levels of openness to trade would follow relatively similar fluctuation patterns.

The results in the previous section suggest that for particular groups of countries in some time periods energy resource prices were not acting as the main coordinating mechanism for emission fluctuations. This could possibly be due to policy responses intended to protect domestic economies from the oil world price. This section investigates the effect of government intervention on the homogeneity of emission fluctuations. Government share of national income is used as a proxy for the level of government intervention in the economy. Therefore, making the assumption that price shielding policies are most likely implemented in countries with high levels of government intervention in their economies.

The analysis in this section is similar to that in the previous section. Trade intensity is used as a measure of openness to trade. The data for government size (government share of Gross Domestic Product (GDP)) and trade intensity were obtained from the Penn World Tables version 6.1 (Heston, Summers and Aten, 2002). Trade intensity is measured as exports plus imports divided by real

GDP. Government size is measured as government final consumption expenditure divided by GDP. Government final consumption expenditure includes all expenditure by general government on individual consumption goods and services (e.g., in-kind transfers: schools, health care), and collective consumption goods and services (e.g., national defence). The indicators are measured in 1996 international dollars to correct for purchasing power parity. Data for these variables were only available for 25 of the 28 developed countries examined in the previous section for the entire period 1950-2000. Developing countries will only be looked at over the 1984-2000 period due to data limitations. The developing country sample for this section consists of 65 of the 104 developing countries examined in the previous section.

Focusing first on the sample of 25 developed countries, Table 4 displays the results of the expanded analysis. The first row of Table 4 displays the homogeneity of emission fluctuations between countries ($\lambda(C)$) for all three time periods. The homogeneity of emission fluctuations decreases in each time period. The per capita emissions for each developed country were then regressed on oil, coal, and natural gas prices (as in equation (13)). PCA was then conducted on the matrix of residuals for each time period; obtaining the homogeneity of fluctuations for the residuals ($\lambda(U)$) displayed in the second row of Table 4. The third row of Table 4 displays the homogeneity of fluctuations for PCA conducted on the matrix of residuals ($\lambda(V)$) from per capita emissions regressed on trade intensity ($TI_{i,t}$)

$$c_{i,t} = a_0 + a_1 TI_{i,t} + v_{i,t} \text{ for } i = 1, 2, \ldots, 25 \tag{16}$$

The fourth row of Table 4 displays the index of homogeneity from PCA conducted on the matrix of residuals ($\lambda(\Phi)$) from per capita emissions regressed on government size ($g_{i,t}$)

$$c_{i,t} = \delta_0 + \delta_1 g_{i,t} + \phi_{i,t} \tag{17}$$

The $\%\Delta H$ in Table 4 is calculated the same way as in equation (15). Looking at the 1950-1966 time period, trade intensity provides the largest negative value of $\%\Delta H$, however, this large value was not found to be statistically significant. Government size also produces a negative but not statistically significant value for $\%\Delta H$. In the 1967-1983 time period, the $\%\Delta H$ for trade intensity is positive and not significant. In the final time period, the $\%\Delta H$ for trade intensity is negative but not significant again. The $\%\Delta H$ for government size is not significant in any of the time periods, despite being large and negative in the 1967-1983 period. All $\%\Delta H$ values for energy prices are statistically significant at the 1% level in all three time periods. This is the same result found for the sample of 28 developed countries studied in Section 3.1. Considering the results of the expanded analysis, energy resource prices appear to be the dominant common factor, and trade intensity and government size do not appear to be common factors at all.

It was found in Section 3.1 that in the latest period the emissions of the developing countries follow the same co-fluctuation pattern as the emissions of the developed countries. It is now useful to examine the common co-fluctuation pattern in greater depth. Table 5 displays the results from an expanded analysis done on the sample of 65 developing countries for the time period 1984-2000. Government size produces the largest negative value for $\%\Delta H$, however, the value is not statistically significant. Openness to trade also produces a large, negative value of $\%\Delta H$, but this value is also not significant. Energy prices produce a large, negative value for $\%\Delta H$ that is statistically significant at the 1% level. These results suggest that for the 1984-2000 time period, energy prices were affecting the dominant common factor and the other two variables were not having a common effect. The results of this section support the results found in Section 3.1, however, due to the data limitations for developing countries it is still unclear what was coordinating the emissions of developing countries in the first two time periods.

4. Conclusions

This paper applied principal component analysis to investigate linkages, in the form of co-fluctuation patterns, of per capita carbon dioxide emissions across countries. The analysis focused on identifying common factors that coordinate the emission fluctuations between countries. The results presented in Section 3.1 indicate a difference in co-fluctuation patterns of emissions between developed and developing countries over the first two time periods, but a common fluctuation pattern in the most recent time period. A possible explanation of this result is that, according to DeVany and Walls (1996), Gulen (1999), and Kleit(2001), among others, regional energy markets became more closely linked throughout the 1980s and 1990s. The common co-fluctuation pattern in the late period is inconsistent with the conclusions found in many of the convergence studies discussed in Section 2 (i.e., the emissions of developing countries behave differently than those of developed countries in relation to convergence). This result may be due, in part, to the convergence studies needing to use the whole time series rather than splitting it into three time periods. If the PCA analysis is conducted on the whole time series, the emissions of developing countries do indeed appear to behave differently than those of developing countries.

Energy prices have coordinated the emissions of developed countries in all periods, however, prices only coordinate the emissions of developing countries globally in the most recent time period. The results of this paper support the findings of McKitrick et al., (in press), since evidence of an emissions offsetting mechanism was found. Furthermore, the strong degree of emissions co-fluctuation combined with energy resource markets as an offsetting mechanism suggests that any global agreement to address climate change requires emissions reduction efforts by all major emitters to be successful. For example, if an agreement only requires emissions reductions by developed countries, as the Kyoto Protocol did, then these reductions and the associated reduced use of energy resources in developed countries will result in increased energy use and corresponding increased emissions in developing countries.

The results of Section 3.2 suggest that regional common fluctuation patterns are driven by energy prices in most cases (all regions except for Africa in 1967-1983); however, energy prices were found to not always be the dominant common factor. The regional results suggest that another unidentified factor also plays a coordinating role. The regional results also suggest that although the emissions of developing countries were not globally coordinated by energy prices in the first two time periods, they were, for the most part, regionally coordinated by energy prices. The results from the expanded analysis in Section 3.3 indicate that openness to trade and the level of government intervention do not play a coordinating role on emissions in any time period for developed countries. And these are not contributing coordinating factors for developing countries in the 1984-2000 time period.

An extension to this research would be to compare the emission fluctuation patterns of China and India with those of the developed countries. This could be done with a similar methodology as the one applied in this paper. Such a study could potentially provide insight on whether future increases of per capita emissions from India and China would be offset by reduced per capita emissions in the developed countries. Another extension would be to apply non-linear principal component analysis in order to consider further moments of the data.

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Table 1: Per capita CO2 emissions descriptive statistics

Statistic	OECD	non-OECD
Countries	28	104
Mean	2.527	1.006
Median	2.335	0.585
StDev	1.134	1.351
Max	5.4	7.7
Min	0.93	0.01

Notes: The statistics are calculated for the year 2000.

Table 2: Homogeneity of emissions fluctuations; Global, developed, and developing

Sample	Period	Emissions, $\lambda(C)$	Residuals, $\lambda(U)$	ΔH	$\%\Delta H$
Global	1950-1966	0.693	0.499	**-0.193**[a]	**-27.94%**[a]
	1967-1983	0.579	0.674	**0.095**[c]	**16.29%**[c]
	1984-2000	0.667	0.376	**-0.291**[a]	**-43.64%**[a]
Developed	1950-1966	0.844	0.534	**-0.310**[a]	**-36.73%**[a]
	1967-1983	0.750	0.668	**-0.082**[c]	**-10.93%**[c]
	1984-2000	0.691	0.492	**-0.199**[a]	**-28.80%**[a]
Developing	1950-1966	0.619	0.559	-0.060	-9.69%
	1967-1983	0.638	0.705	0.067	10.50%
	1984-2000	0.689	0.463	**-0.291**[a]	**-32.80%**[a]

Notes: $\lambda(C)$ is the proportion of variation explained by the first principal component (PC1) from the emissions matrix, C. $\lambda(U)$ is the proportion of variation explained by the PC1 from the matrix of residuals from the price regressions (see equation (13)). ΔH is the difference between $\lambda(U)$ and $\lambda(C)$ (see equation (14)). $\%\Delta H$ is the percent change between $\lambda(C)$and $\lambda(U)$ (see equation (15)). The superscripts a, b, c denote significance at the 1%, 5%, and 10% levels respectively. The associated critical values can be found in Table C.8 located in Appendix C.

Table 3: Homogeneity of emissions fluctuations; Regional groupings

Sample	Period	Emissions, $\lambda(C)$	Residuals, $\lambda(U)$	ΔH	$\%\Delta H$
North America	1950-1966	0.753	0.453	**-0.300**[a]	**-39.84%**[a]
	1967-1983	0.426	0.623	**0.197**[a]	**46.24%**[a]
	1984-2000	0.740	0.674	**-0.066**[c]	**-8.92%**[c]
Western Europe	1950-1966	0.835	0.554	**-0.281**[a]	**-33.65%**[a]
	1967-1983	0.787	0.646	**-0.141**[b]	**-17.92%**[a]
	1984-2000	0.624	0.484	**-0.140**[b]	**-22.44%**[a]
Eastern Europe	1950-1966	0.971	0.875	**-0.096**[a]	**-9.89%**[a]
	1967-1983	0.935	0.678	**-0.257**[a]	**-27.49%**[a]
	1984-2000	0.951	0.772	**-0.179**[a]	**-18.82%**[a]
Africa	1950-1966	0.809	0.459	**-0.350**[a]	**-43.30%**[a]
	1967-1983	0.919	0.934	0.015	1.63%
	1984-2000	0.637	0.509	**-0.128**[b]	**-20.09%**[b]
Middle-east	1950-1966	0.809	0.892	**0.083**[a]	**10.26%**[b]
	1967-1983	0.972	0.910	**-0.062**[a]	**-6.38%**[a]
	1984-2000	0.811	0.660	**-0.151**[a]	**-18.62%**[a]
Central & South America	1950-1966	0.793	0.457	**-0.336**[a]	**-42.37%**[a]
	1967-1983	0.871	0.934	**0.063**[b]	**7.23%**[b]
	1984-2000	0.589	0.498	**-0.091**[b]	**-15.45%**[c]
Asia & Oceania	1950-1966	0.810	0.955	**0.145**[a]	**17.90%**[a]
	1967-1983	0.673	0.854	**0.181**[a]	**26.89%**[a]
	1984-2000	0.920	0.846	**-0.074**[a]	**-8.04%**[a]

Notes: See notes for Table 2. The superscripts a, b, and c denote significance at the 1%, 5%, and 10% levels respectively. The associated critical values can be found in Tables C.9 and C.10 located in Appendix C.

Table 4: Expanded analysis: Developed countries

25 OECD Countries	1950-1966	1967-1983	1984-2000
Emissions, $\lambda(C)$	0.826	0.765	0.679
Price Residuals, $\lambda(U)$	0.534	0.668	0.499
$\%\Delta H$ for U	**-35.35%**[a]	**-12.68%**[a]	**-26.51%**[a]
Trade Residuals, $\lambda(V)$	0.420	0.83	0.575
$\%\Delta H$ for V	-49.15%	8.50	-15.32%
Gov't Size Residuals, $\lambda(\Phi)$	0.716	0.448	0.683
$\%\Delta H$ for Φ	-13.32%	-41.44%	0.59%

Notes: Sample of 25 OECD countries. Row 1 displays the homogeneity of emission fluctuations. Row 2 displays the homogeneity of fluctuation for the matrix of residuals from the price regressions (see equation (13)). Row 3 displays the homogeneity of fluctuation for the matrix of residuals from the trade intensity regressions (see equation (16)). Row 4 displays the homogeneity of fluctuation for the matrix of residuals from the government size regressions (see equation (17)). $\%\Delta H$ is the percent change between $\lambda(C)$ and the $\lambda(\cdot)$ for whichever matrix of residuals is in question. The superscript a denotes significance at the 1% level. The associated critical values can be found in Table C.11 located in Appendix C.

Table 5: Expanded analysis: Developing countries

65 non-OECD countries	1984-2000
Emissions, $\lambda(C)$	0.733
Price residuals, $\lambda(U)$	0.446
$\%\Delta H$ for U	**-39.15%**[a]
Trade residuals, $\lambda(V)$	0.473
$\%\Delta H$ for V	-35.47%
Gov't size residuals, $\lambda(\Phi)$	0.425
$\%\Delta H$ for Φ	-42.02%

Notes: Sample of 65 developing countries. For Table explanation, see notes for Table 4. The superscript a denotes significance at the 1% level. The associated critical values can be found in Table C.12 located in Appendix C.

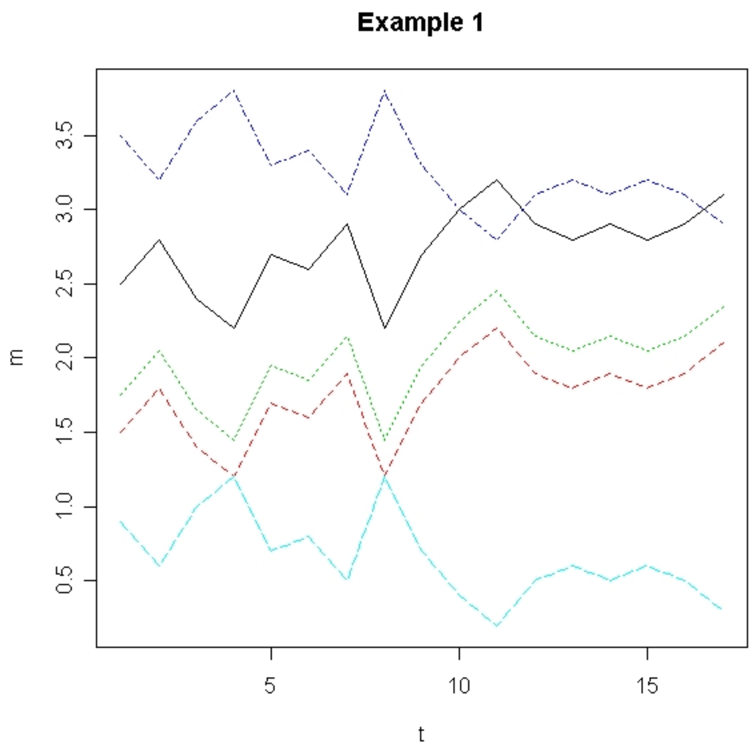

Figure 1: PCA Example 1
Notes: Three series have perfect co-movement, while the other two series move opposite. The five series are perfectly co-fluctuating. Principal component analysis conducted on the 5 series produces a first principal component that explains 100% of the variation in the data.

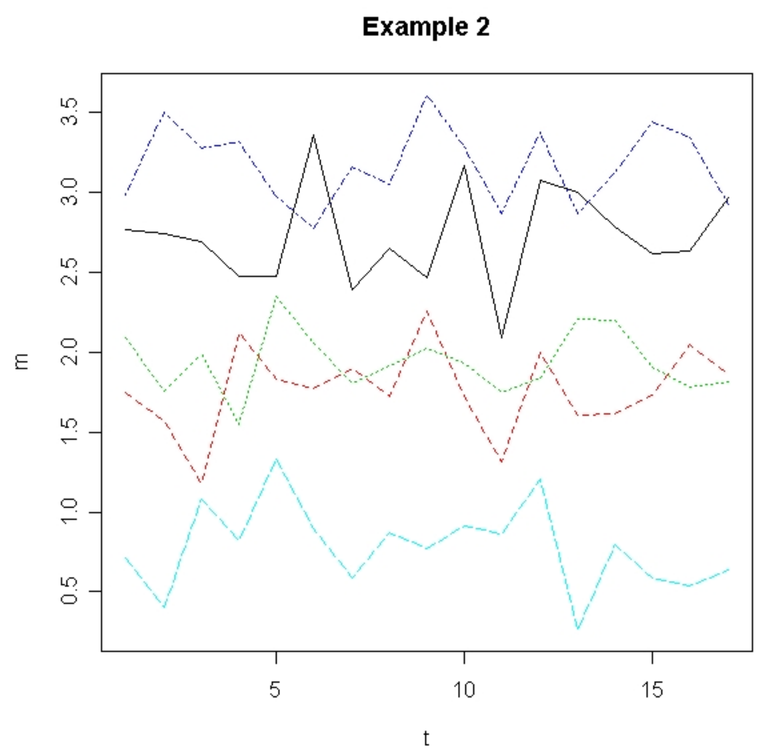

Figure 2: PCA Example 2
Notes: The fluctuations for the five series are randomly drawn from a normal distribution with zero mean and standard deviation of 0.29. PCA conducted on the five series produces a PC1 that explains 32.7% of the variation in the data.

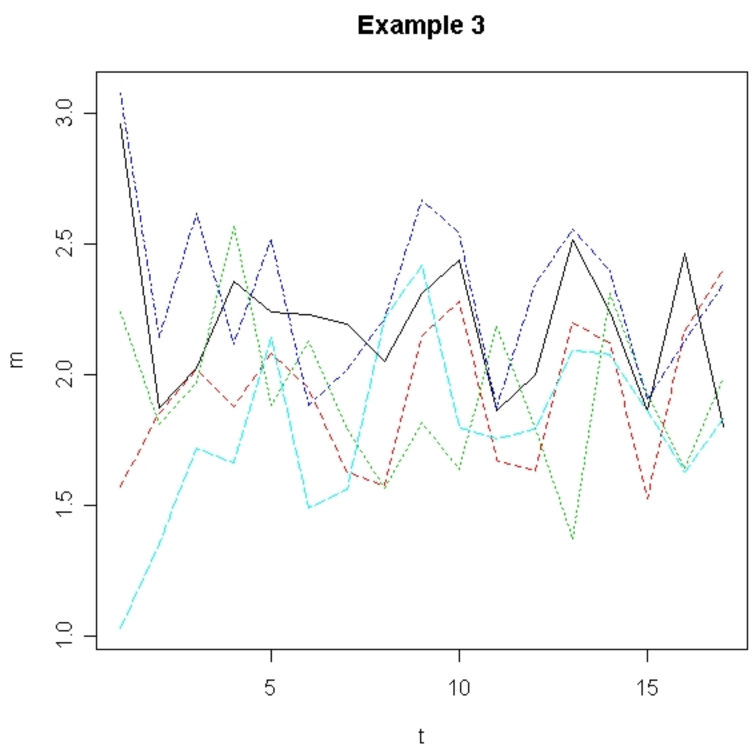

Figure 3: PCA Example 3
Notes: The data is characterized by sigma convergence and random fluctuations. However, PCA on the data produces a PC1 that explains only 35% of the variation in the data.

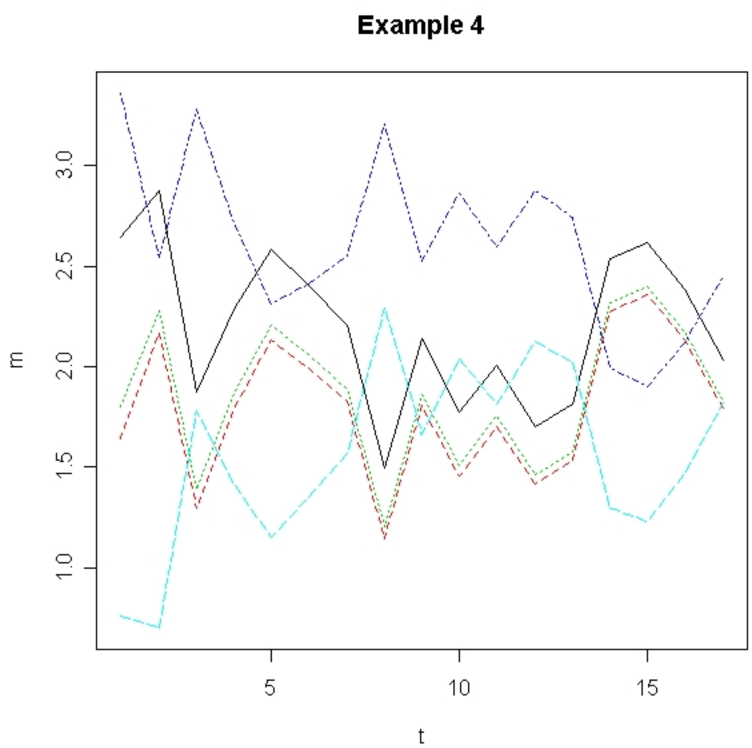

Figure 4: PCA Example 4
Notes: The data is characterized by sigma convergence and co-fluctuation. PCA on the data produces a PC1 that explains 80.1% of the variation in the data.

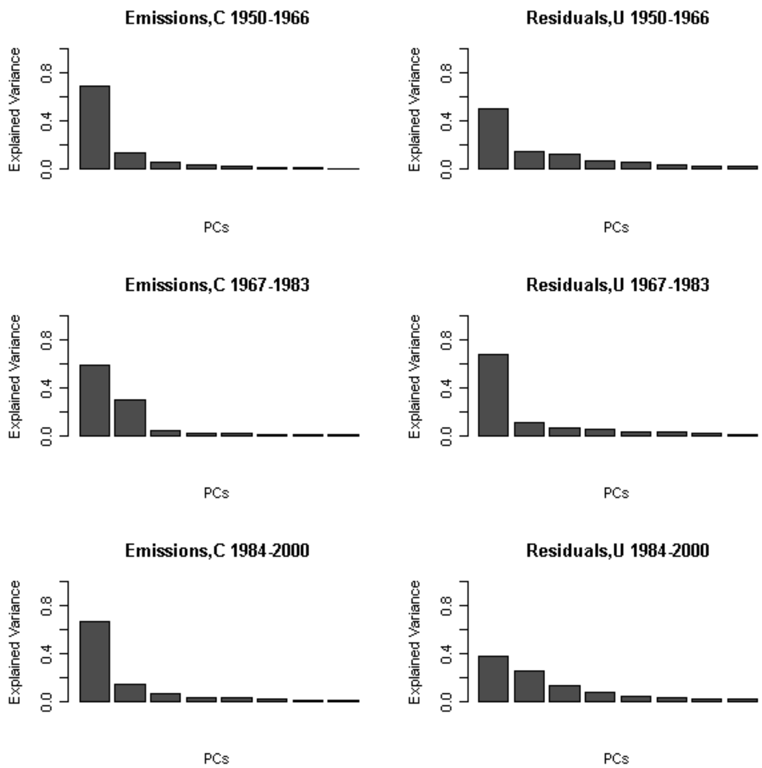

Figure 5: Global sample scree plots

Notes: The graphs on the left are the 'scree' plots from PCA conducted on the emissions for the global sample of 132 countries. The graphs on the right are the 'scree' plots from PCA conducted on the matrix of residuals from the price regressions (see equation (13)). Each bar represents the proportion of variation attributed to a particular principal component. The bars are listed in decreasing order of importance (the left most bar for each graph is attributed to the first principal component). Looking at the scree plots on the left (right), the height of the largest bar of each plot is $\lambda(C)$ $(\lambda(U))$.

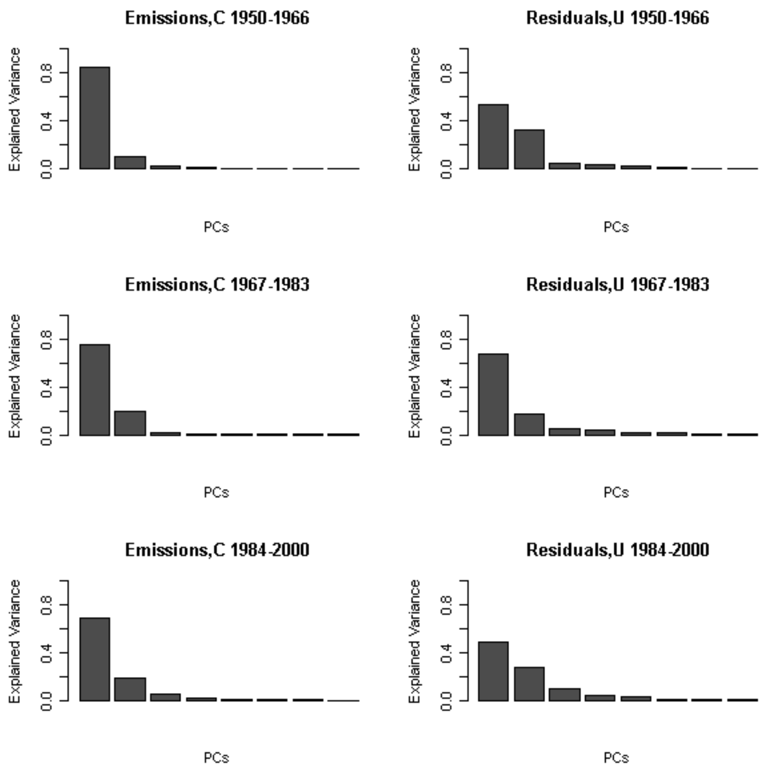

Figure 6: Developed sample scree plots
Notes: The graphs are the scree plots for the PCA conducted on the data for the 28 developed countries. For further explanation see the notes for Figure 5.

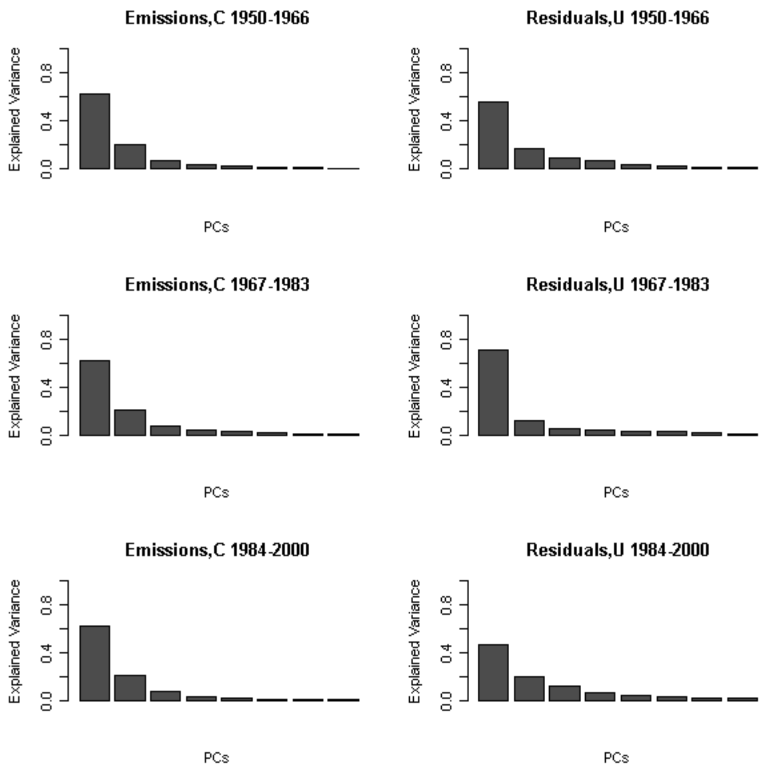

Figure 7: Developing sample scree plot

Notes: The graphs are the scree plots for the PCA conducted on the data for the 104 developing countries. For further explanation see the notes for Figure 5.

Appendix A. Data Information

This study uses annual data of per capita carbon dioxide emissions, energy resources, and macroeconomic variables from 1950 to 2000. Each variable is discussed in this appendix. The chosen time interval was selected as a solution to the trade-off between the number of countries in the cross-section and the number of years of emission data (i.e. more countries could be included if the data was taken from 1960).

Appendix A.1. Carbon dioxide emissions data

The emissions data were obtained from the Carbon Dioxide Information and Analysis Center (CDIAC, Marland et al. (2003)), at the Oak Ridge National Laboratory in Oak Ridge, Tennessee. The emissions data are measured in metric tonnes of carbon per capita. It includes the CO2 emissions produced from fossil fuel burning, gas flaring, and cement manufacture. It does not include the emissions from bunker fuels used in transport. The data originally were available for 140 countries, however, the emissions of the USSR were removed. The emissions of seven countries that exhibited any observations greater than 15 tonnes of carbon per capita (Brunei, Falkland Islands, Kuwait, Qatar, US Virgin Islands, United Arab Emirates, Wake Island) were removed. After removing the USSR and the outlier countries, the emission sample contains 132 countries (28 OECD, 104 non-OECD).

Appendix A.2. Energy resource price data

Price data for crude oil, natural gas, and coal were obtained from the Annual Energy Review 2006 produced by the Energy Information Administration (EIA) of the United States government. The prices for crude oil are the average annual crude oil domestic first purchase prices for the United States (nominal USD per barrel). The natural gas prices are the average annual US natural gas wellhead prices (nominal USD per thousand cubic feet). The coal prices are the average annual US free-on-board prices of coal at the point of first sale (nominal USD per short ton). The nominal prices were converted into real prices (constant year 2000 USD) using Consumer Price Index (CPI) data from the Bureau of Labor Statistics, US Department of Labor (Series ID: CUUR0000A0, URL: http://data.bls.gov/cgi-bin/srgate).

The results of the Kwiatkowski, et al. (1992) test suggest that all three energy price series are stationary at the 5% significance level. The results are listed in Table A.6. Furthermore, the results of the Elliot, et al. (1996) test, displayed in Table A.7, suggest that none of the three series have a unit root.

Table A.6: KPSS Stationarity Test on Energy Prices

		Model	
Variable	Period	Short (3 lags)	Long (10 lags)
Oil	1950-2000	0.2801	0.1682
Coal	1950-2000	0.2138	0.1144
Gas	1950-2000	**0.8711**[a]	**0.4138**[c]

Notes: The null hypothesis is that the series in question is stationary. The superscripts a, b, c denote significance at the 1%, 5%, and 10% levels respectively.

Table A.7: ERS Unit Root Test on Energy Prices

		P-Test		DF-GLS	
Variable	Period	Constant	Trend	Constant	Trend
Oil	1950-2000	**1.1993**[a]	**3.7016**[a]	**-2.0435**[b]	-2.3031
Coal	1950-2000	**0.5323**[a]	**1.5857**[a]	**-2.235**[b]	-2.3032
Gas	1950-2000	**2.4107**[b]	**2.0908**[a]	-0.8191	**-3.1473**[b]

Notes: The null hypothesis is that the series in question has a unit root. The superscripts a, b, c denote significance at the 1%, 5%, and 10% levels respectively.

Appendix A.3. Macroeconomic data

Data for government size and trade intensity were obtained from the Penn World Tables version 6.1. Government size is measured as government final consumption expenditure divided by real gross domestic product (GDP). Government final consumption expenditure includes all expenditure by general government on individual consumption goods and services (e.g. in-kind transfers: schools, health care), and collective consumption goods and services (e.g. national defence). Trade intensity is measured as exports plus imports divided by real GDP. Both trade intensity and government size are measured in constant 1996 international dollars to correct for purchasing power parity. Data for these indicators were only available for 25 OECD countries for the period 1950-2000, and 65 non-OECD countries for the period 1984-2000.

Appendix B. List of Countries

Appendix B.1. Developed Sample:

Australia, Austria, Belgium, Canada, Denmark, Finland, France (including Monaco), Germany, Greece, Hungary, Iceland, Ireland, Italy (including San Marino), Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Republic of Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States of America.

Appendix B.2. Developing Sample:

Afghanistan, Albania, Algeria, Angola, Argentina, Bahamas, Bahrain, Barbados, Belize, Bermuda, Bolivia, Brazil, Bulgaria, Cape Verde, Cayman Islands, Chile, China, Colombia, Costa Rica, Cuba, Cyprus, Democratic People's Republic of Korea, Democratic Republic of the Congo, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Faeroe Islands, Fiji, French Guiana, Gambia, Ghana, Gibraltar, Greenland, Grenada, Guadeloupe, Guam, Guatemala, Guinea Bissau, Guyana, Haiti, Honduras, Hong Kong, India, Indonesia, Iraq, Islamic Republic of Iran, Israel, Jamaica, Jordan, Kenya, Lebanon, Liberia, Libyan Arab Jamahiriyah, Macau, Madagascar, Malta, Martinique, Mauritius, Mongolia, Morocco, Mozambique, Myanmar, Nepal, New Caledonia, Nicaragua, Nigeria, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Puerto Rico, Republic of Cameroon, Reunion, Romania, Saint Helena, Saint Lucia, Samoa, Sao Tome & Principe, Saudi Arabia, Seychelles, Sierra Leone, Solomon Islands, South Africa, Sri Lanka, St. Pierre & Miquelon, St. Vincent & The Grenadines, Sudan, Suriname, Syrian Arab Republic, Taiwan, Thailand, Togo, Tonga, Trinidad & Tobago, Tunisia, Uganda, Uruguay, Vanuatu, Venezuela.

Appendix C. Bootstrap Simulations

To increase the definitiveness of the analysis, it is necessary to test the null hypothesis that energy resource prices are not a common factor (i.e.H_0: $\Delta H = 0$ and $\%\Delta H = 0$) against the alternative hypotheses that prices are the dominant factor (i.e. H_1: $\Delta H < 0$ and $\%\Delta H < 0$) and prices are not the dominant factor, but are a common factor (i.e. H_2: $\Delta H > 0$ and $\%\Delta H > 0$). The null hypothesis can be tested by using the bootstrap (Efron (1979)) to obtain the empirical distribution of ΔH and $\%\Delta H$. Each bootstrap sample C^{*j} is obtained by resampling the centered emissions matrix with replacement. To maintain the correlation structure accross countries, the emissions matrix is resampled holding the cross-sectional dimension constant.

PCA is then undertaken on C^{*j} to obtain $\lambda(C^{*j})$. Then C^{*j} is regressed on resource prices to obtain the matrix of residuals, U^{*j}. PCA is then undertaken on U^{*j} to obtain $\lambda(U^{*j})$. Values of ΔH^* and $\%\Delta H^*$ are then calculated. The process is repeated $B = 999$ times to produce 999 bootstrap estimates of ΔH^* and $\%\Delta H^*$.

Critical values for the null hypothesis can then be calculated as the 0.05%, 2.5%, and 5% quantiles of the simulated estimates considering H_1 and as the 99.5%, 97.5%, and 95% quantiles of the simulated estimates considering H_2. The simulation process is repeated for every group of countries and every time period. Table C.8 contains the critical values for the simulations for the global, OECD, and non-OECD samples of countries. Tables C.9 and C.10 contain the critical values for the regional groups of countries. Table C.11 contains the critical values for the expanded analysis undertaken for the group of 25 OECD countries. Table C.12 contains the critical values for the expanded analysis undertaken for the group of 65 developing countries.

Table C.8: Bootstrap Critical Values; Global, Developed, Developing

		Global Sample					
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.156	0.085	-0.089	0.07	-0.073	0.06
	$\%\Delta H$	-21.53	13.83	-12.85	11.09	-10.17	8.79
1967-1983	ΔH	-0.14	0.132	-0.084	0.107	-0.07	0.091
	$\%\Delta H$	-20.38	23.4	-13.68	18.56	-10.88	15.63
1984-2000	ΔH	-0.145	0.093	-0.098	0.07	-0.072	0.058
	$\%\Delta H$	-21.15	13.9	-14.24	10.52	-10.51	8.66
		Developed Country Sample					
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.119	0.058	-0.072	0.043	-0.051	0.038
	$\%\Delta H$	-13.64	6.87	-8.47	5.07	-6.04	4.48
1967-1983	ΔH	-0.135	0.134	-0.097	0.077	-0.071	0.06
	$\%\Delta H$	-18.13	18.81	-13.26	11.06	-9.79	8.17
1984-2000	ΔH	-0.137	0.101	-0.088	0.08	-0.065	0.068
	$\%\Delta H$	-18.89	16.24	-12.87	12.01	-9.52	9.91
		Developing Country Sample					
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.121	0.121	-0.085	0.088	-0.066	0.073
	$\%\Delta H$	-21.5	24.34	-14	16.21	-10.37	12.33
1967-1983	ΔH	-0.126	0.128	-0.088	0.095	-0.073	0.084
	$\%\Delta H$	-18.1	21.91	-13.71	15.37	-10.94	13.03
1984-2000	ΔH	-0.151	0.09	-0.097	0.066	-0.071	0.056
	$\%\Delta H$	-21.61	13.12	-14.02	9.72	-9.91	8.18

Table C.9: Bootstrap Critical Values; Regional

North America							
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.15	0.089	-0.095	0.064	-0.068	0.057
	$\%\Delta H$	-20	12.69	-12.22	8.63	-9.16	7.55
1967-1983	ΔH	-0.102	0.142	-0.077	0.11	-0.06	0.085
	$\%\Delta H$	-18.5	26.85	-14.65	21.03	-10.85	17
1984-2000	ΔH	-0.127	0.11	-0.088	0.074	-0.064	0.06
	$\%\Delta H$	-17.6	16.91	-12.64	10.74	-8.69	8.43

Western Europe							
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.122	0.06	-0.072	0.045	-0.055	0.037
	$\%\Delta H$	-14.51	7.5	-8.73	5.4	-6.55	4.46
1967-1983	ΔH	-0.142	0.113	-0.092	0.063	-0.07	0.049
	$\%\Delta H$	-17.86	15.19	-11.76	8.54	-8.88	6.62
1984-2000	ΔH	-0.144	0.107	-0.092	0.084	-0.068	0.072
	$\%\Delta H$	-21.6	18.54	-14.23	13.79	-10.4	11.67

Eastern Europe							
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.033	0.014	-0.018	0.01	-0.013	0.009
	$\%\Delta H$	-3.42	1.43	-1.88	1.09	-1.39	0.92
1967-1983	ΔH	-0.075	0.033	-0.042	0.025	-0.028	0.02
	$\%\Delta H$	-8.2	3.6	-4.7	2.69	-3.05	2.15
1984-2000	ΔH	-0.044	0.027	-0.027	0.018	-0.02	0.015
	$\%\Delta H$	-4.66	2.86	-2.9	1.9	-2.15	1.65

Africa							
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.117	0.055	-0.074	0.046	-0.051	0.04
	$\%\Delta H$	-14.73	6.81	-8.77	5.61	-6.37	4.98
1967-1983	ΔH	-0.093	0.06	-0.047	0.037	-0.034	0.03
	$\%\Delta H$	-11.38	8.24	-5.39	5	-3.98	3.42
1984-2000	ΔH	-0.137	0.099	-0.101	0.076	-0.08	0.068
	$\%\Delta H$	-20.92	16.73	-15.54	12.08	-12.05	10.51

Table C.10: Bootstrap Critical Values; Regional Cont'd.

		The Middle East					
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.134	0.083	-0.093	0.059	-0.066	0.049
	$\%\Delta H$	-19.39	12.77	-11.91	7.6	-8.2	6.21
1967-1983	ΔH	-0.031	0.017	-0.019	0.01	-0.012	0.008
	$\%\Delta H$	-3.23	1.76	-1.93	1.07	-1.26	0.81
1984-2000	ΔH	-0.141	0.073	-0.078	0.058	-0.063	0.046
	$\%\Delta H$	-15.99	9.65	-9.85	7.24	-7.58	5.54
		Central and South America					
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.138	0.078	-0.078	0.059	-0.063	0.047
	$\%\Delta H$	-18.64	10.93	-10	7.82	-8.16	6.27
1967-1983	ΔH	-0.099	0.066	-0.06	0.048	-0.046	0.039
	$\%\Delta H$	-11.55	7.63	-6.86	5.51	-5.23	4.47
1984-2000	ΔH	-0.134	0.104	-0.091	0.08	-0.073	0.071
	$\%\Delta H$	-21.69	18.23	-15.78	14.84	-12.15	11.9
		Asia and Oceania					
		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
1950-1966	ΔH	-0.123	0.1	-0.083	0.069	-0.064	0.057
	$\%\Delta H$	-15.78	13.23	-10.12	8.99	-7.98	6.96
1967-1983	ΔH	-0.106	0.151	-0.084	0.111	-0.066	0.093
	$\%\Delta H$	-15.71	25.45	-11.5	17.69	-9.45	14.53
1984-2000	ΔH	-0.059	0.032	-0.041	0.025	-0.028	0.02
	$\%\Delta H$	-6.26	3.56	-4.49	2.69	-3.05	2.14

Table C.11: Bootstrap Critical Values; Expanded Analysis, Developed Countries

		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
$\%\Delta H$ for U	1950-1966	-13.64	6.87	-8.47	5.07	-6.04	4.48
	1967-1983	-18.13	18.81	-13.26	11.06	-9.79	8.17
	1984-2000	-21.15	13.9	-14.24	10.52	-10.51	8.66
$\%\Delta H$ for V	1950-1966	-54.33	-43.3	-53.72	-45.02	-53.22	-45.99
	1967-1983	-8.63	39.21	-6.35	29.82	-4.73	25.43
	1984-2000	-33.18	13.02	-30.37	1.48	-28.73	-2.32
$\%\Delta H$ for Φ	1950-1966	-22.17	-3.37	-21.12	-6.29	-20.26	-7.95
	1967-1983	-50.66	-24.82	-49.43	-29.89	-48.55	-32.27
	1984-2000	-20.56	34.36	-17.23	20.64	-15.27	16.12

Table C.12: Bootstrap Critical Values; Expanded Analysis, 65 Developing Countries

		α =1%		α =5%		α =10%	
	Bounds:	Lower	Upper	Lower	Upper	Lower	Upper
$\%\Delta H$ for U	1984-2000	-46.44.57	25.81	-40.44	18.65	-38.46	8.23
$\%\Delta H$ for V	1984-2000	-44.38	-21.3	-43.18	-25.33	-42.68	-27.66
$\%\Delta H$ for Φ	1984-2000	-49.95	-29.19	-48.87	-32.81	-48.42	-34.91