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Tests of the EKC Hypothesis using CO_2 Panel Data

Jianping Shi

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REPA Research Group
Department of Economics
University of Victoria
PO Box 1700 STN CSC
Victoria, BC V8W 2Y2 CANADA
Ph: 250.472.4415
Fax: 250.721.6214
http://repa.econ.uvic.ca

Abstract

Environmental Kuznets Curve depicts the long-term relationship between pollution and economic growth. It hypothesizes that during the initial stages of economic growth environmental quality will deteriorate, then, after reaching some turning point, it will improve as the economy grows. In the past decade, lots of empirical literature provided both supports and criticism to this hypothesis. However, as we know from econometrics, when data contain stochastic trends, the conclusions drawn from such analysis might be meaningless. In this paper, we test the stationarities of a number of key variables used in such analyses using a panel data set for 50 countries over 50 years. The tests with different null hypothesis find that the data are stochastically trending in the time-series dimension. Given this, the regressions and interpretation of pollution-growth models should be interpreted with care. Further tests on cointegration of appropriate model are required.

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1. INTRODUCTION

In 1991, Grossman and Krueger presented their pioneering paper addressing the long-term relationship between global pollution and economic growth.[1] Based on cross-sectional data for 42 countries, they found an "inverted-U" shaped relationship between a variety of indicators of environmental pollution or resource depletion and the level of per capita income, showing that pollution is expected to increase considerably during the first stage of economic development, but then, after reaching a peak (or "turning point"), it declines with higher per capita GDP. Given its similarity to the relationship between income inequality and economy growth advocated by Kuznets in 1955, this model is called an Environmental Kuznets Curve (EKC).

In the past decade, great efforts have been put into testing the EKC hypothesis by applying different models (linear, parametric, semi-parametric, non-parametric and fuzzy), analyzing various pollutants (SO_2, CO_2, NH_4, *etc.*) and using various types of data (time series, cross-section and panel). Yet, the exact form of the model remains inconclusive and the results are mixed.

Not until recently, the classical regression analysis assumed that all the variables involved were stationary. However, Nelson and Plosser (1982) pointed out that most of the macroeconomic data are random walks. Appropriate methods of regression depend on how the variables are integrated. In some cases, the residual from a regression of integrated variables is also integrated. This violates the assumptions of classical regression model that the residual is independently identically distributed. Therefore, the distribution of the regression parameters is highly non-standard. Figure 1 illustrates the problem that arises. Two variables x and y are both time series: y has been smoothly increasing over 50 years, while x increases sharply in the first 30 years, then after a sudden drop, it oscillates around a certain level in the following decades. A model of $y=\alpha+\beta x+\varepsilon$ is estimated, with the "dotted" curve depicting the pattern of the residuals. It

1 The paper named *Environmental Impacts of a North American Free Trade Agreement* was first presented in the Conference on the U.S. – Mexico Free Trade Agreement in 1991, and was published as NBER working paper (No. 3914). In 1993, it was collected in *The US-Mexico Free Trade Agreement* (Cambridge Mass, MIT Press). Later, this paper was expanded upon in Grossman and Krueger (1995), which is a milestone in EKC research.

is obviously that the residual is not white noise. The regression and interpretation of the model is "spurious".

This paper tests the stationarity of a number of key variables using a global panel data set of carbon dioxide and economic growth of 50 countries over 50 years. Both individual series and panel data are tested. Different null hypotheses are also applied to ensure the power of tests. All the tests show that the data are integrated in the time-series dimension. This implies that further cointegration tests are required before one can properly undertake a regression analysis.

This paper is organized in the following way: Section 2 presents a literature review of both the theoretical and the empirical studies on the Environmental Kuznets Curve. Section 3 introduces the data and executes the unit roots test to the variables. Section 4 discusses some cointegration tests; in Section 5, conclusion is drawn.

2. LITERATURE REVIEW

At the beginning of 1990s, environmentalists voiced their concerns about a potential North American Free Trade Agreement (NAFTA). They argued that the expansion of markets and economic activities, the change of composition of the economy and the decrease of US regulatory standards on environment might lead to more pollution and faster depletion of scarce natural resources. In 1993, Grossman and Krueger presented an empirical paper on the conference of the U.S.–Mexico Free Trade Agreement, illustrating how a reduction in trade barriers generally affects the environment by expanding the scale, altering the composition and changing in the technology of the economy.

Grossman and Kruger (1993) constitute the seminal work on the Environmental Kuznets Curve (EKC). They analyzed data for SO_2, suspended particulate matter (SPM) and particulates (smoke) for 1977, 1982 and 1988. The data were from Global Environmental Monitoring System (GEMS), which monitors air quality in urban areas throughout the world. Grossman and Kruger did regressions on both random and fixed effects models using a cubic function form. A linear time trend, a variable of openness and dummy variables of location were also included. They found that concentrations of two of the three pollutants, SO_2 and particulates, rise with per capita GDP at low levels of national income, and then fall as per capita GDP grows. The turning points for each of them are $4,119 (1985 U.S. dollars) and $5,000 (1985 U.S. dollars). The estimated curves imply an inverted U shaped relationship. Meanwhile, the SPM was found to fall in response to increases in per capita GDP at low levels of economic development. Then after GDP per capita reaches $9,000, economic growth has no further effect on the concentration of SPM. Grossman and Kruger argue that economic growth tends to alleviate pollution problems once a country's per capita income reaches certain level ($4,000 to $5,000 1985 U.S. dollars in this paper). They also predict that, because the free trade agreement with the U.S. and Canada would improve the economic growth of Mexico, whose per capita GDP was already $5,000 (1985 US dollars) at that time, this country would intensify its efforts to alleviate its environmental problems, so that it pollution level would decrease from that point on.

In the following decades, many attempts have been made to evaluate the impact of economic growth on environmental quality. The literature is both theoretical and empirical.

2.1 Theoretical Literature Review

Theoretical explanations as to why environmental degradation should first increase and then decline with income have focused on three of factors: the effects of scale and structure of the economy; the link between the demand for environmental quality and income; and policies and regulations related to environmental degradation.

As income grows, the scale of an economy tends to become larger. As Grossman (1995) suggested, a developing society requires increasing output, therefore more inputs and more natural resources. In addition, more output also implies increased wastes and emissions as a by-product of the economic activity, which worsens the environmental quality. This is the so-called *scale effect*.

The structure of the economy also tends to change with the development of the economy. As Panayotou (1993) points out, environmental degradation tends to increase as the structure of the economy changes from rural to urban, from agricultural to industrial. But it starts falling with the second structural change from energy-intensive heavy industry to services and technology-intensive industry. Finally, technological progress leads to the substitution of obsolete and dirty technologies with cleaner ones, which also improves the quality of the environment. This is the *technology effect*. When the technology effect dominates the scale effect, the pollutant level would increase during the period of first structural change of economy and then decrease during the second stage of structural change. Therefore the inverted U curve comes into being.

Some of the theoretical literature has focused on household preferences environmental quality with the pollutant level. If these preferences following the assumption that the damage from extra pollution grows as income grows, then such preferences can be illustrated as an important factor of bending back down of the pollution-growth curve. McConnell (1997) studies the combined effects of preferences; increasing costs of pollution control and the declining value of extra consumption as per capita incomes grow. Applying a method of non-market valuation, McConnell shows that a high-income elasticity of demand for environmental quality is neither necessary nor sufficient for the EKC. Besides preferences, the assimilative capacity of the environment and the cost of abatement are also important influences on the pollution-growth relationship.

Others argue that the method of decomposing economic development into its components, and study the bilateral relationship between pollution and each component is only partially right. As Panayotou (1997) points out, "… they focus only on the scale and industrialization effects and ignore the abatement effect of higher incomes." (P.429) In the same paper, the author maintains that the findings from models only including economic growth variables could lead to the unintended and misleading interpretation that some countries can grow out of their environmental problems without the establishment of conscious environmental policies. By taking explicit policy determinants into consideration, Panayotou (1997) finds that better policies, such as more secure property rights and better enforcement of contracts and effective environmental regulations, can help flatten the EKC and reduce the environmental price of economic growth.

While some economists seek to explain the explanation of the inverted-U growth-pollution relationship, others cast doubt on the shape of the curve itself. Dasgupta *et al*. (2002) examine different EKC scenarios in the recent literature and provide theoretical explanations for different views. Some research shows that the pollution-growth curve rises asymptotically to same maximum pollution level, never coming down again. The EKC curves of some countries or pollutants maintain a high level while others maintain a low level of per capita pollutants. The cumulative effect is inverted U shaped, because the EKC is just a snapshot of a dynamic process. This is the so-called "race-to-the-bottom" curve. Pessimists argue that, even if certain pollutants are reduced as income increases, industrial society continuously creates new, unregulated and potentially toxic pollutants. Then the overall environmental risks from these new pollutants may continue to grow even if some sources of pollution are reduced. Holtz-Eakin and Selden (1995) named it the "new toxics" phenomenon. Meanwhile, some recent research has fostered an optimistic critique of the relationship. They suggest that the level of the curve is actually dropping and shifting to the left, as growth generates less pollution in the early stages of industrialization and pollution begins falling at lower income levels because of the technology overflow and economy globalization. In a comprehensive survey by Stern (1996), the author points out that only a subset of pollutants can apply the model of inverted-U curve, such as sulfur dioxide and suspended particulates.

2.2 Empirical Literature Review—Early Research

Early empirical research (1993-1996) is focused on testing different pollutant indicators of different countries with simple linear parametric model, trying to see if EKC is a universal relationship between pollution and growth. Shafik and Bandyopadhyay (1992), Selden and Song (1994), Panayotou (1993), Cropper and Griffiths (1994), and Meyer *et al.* (2003) are examples of such literature.

Shafik and Bandyopadhyay (1992) estimated EKCs for nine different indicators from a panel data set: lack of clean water, lack of urban sanitation, ambient levels of suspended particulate matter, ambient sulfur dioxides, change in forest area, dissolved oxygen in rivers, faecal coliforms in rivers, municipal waste per capita, and carbon emissions per capita (converted from CO_2 emissions). Data coverage and sources varied between the different indicators.

They used three different functional forms: log-linear, log-quadratic and logarithmic cubic polynomial. The Ordinary Least Square (OLS) estimations were applied. The dependent variables included different forms of GDP per capita in purchasing power parity (PPP) dollars and a time trend and site-related variables. In each case, the dependent variable has not been transformed. Shafik and Bandyopadhyay also carried out a number of additional regressions adding various policy variables such as trade orientation and electricity prices. The results for these were mixed.

Some of their results are as follows: Lack of clean water and lack of urban sanitation decrease monotonically with increasing income. The indicator of deforestation is insignificantly related to the income terms. River quality tends to be worsening with increasing income. SO_2 and SPM conform to the EKC hypothesis. The turning points for both pollutants are found for income levels of between \$3,000 and \$4,000. Finally, both municipal waste and carbon emissions per capita increase unambiguously with rising income.

Selden and Song (1994) estimated EKCs for four pollutants: SO_2, NO_x, SPM and CO using longitudinal data from World Resources (1991). They focus on the model expressed as: $m_{it} = \beta_0 + \beta_1 y_{it} + \beta_2 y_{it}^2 + \beta_d d_{it} + \varepsilon_{it}$, and apply different control variables as d_{it} including population density, different period dummies. One of the regressors, population density, is significant in their analysis, showing that in countries with low population densities there will be less pressure to adopt stringent environmental standards and emissions due to transportation will be higher. They find substantial support for the inverted U hypothesis, thereby providing independent confirmation of previous findings. The estimated turning points are all very high compared to other studies: SO_2, $8,709; NO_x, $11,217; SPM, $10,289; and CO, $5,963.

Panayotou (1993) estimated EKCs for SO_2, NO_x, SPM and deforestation. His study employs only cross sectional data and GDP is in nominal 1985 US dollars. The data on emission for developing countries were estimated from fuel use and fuel mix data. Deforestation was measured as the mean annual rate of deforestation in the mid 1980s. There are 68 counties in the deforestation sample and 54 in the pollution sample.

The models for the three pollutants are in logarithmic forms with quadratics in income per capita. For deforestation Panayotou uses a translog function in population density, a dummy variable for tropical countries and income per capita. All the estimated curves are inverted Us. In his results, the turning point for deforestation is $823 per capita. Deforestation rates were significantly greater in tropical countries. Deforestation was also higher in countries with higher population densities. For SO_2 emissions the turning point is around $3,000 per capita, for NO_x around $5,500 per capita, and for SPM around $4,500 per capita.

Cropper and Griffiths (1994) estimate three regional (Africa, Latin America and Asia) EKCs for deforestation using panel data for 64 countries over a thirty-year period. The dependent variable is the negative of the percentage change in forest area between two years. The independent variables in each regression are rural population density, percentage change in population, timber price, per capita GDP, percentage change in per capita GDP in PPP dollars, square of per capita GDP, a dummy variable for each country, and a time trend. Neither the population growth rate nor the time trend was significant in either Africa or Latin America, and the price of tropical logs was insignificant, while in the Asian regression were significant. There two conclusions are drawn from Cropper and Griffiths' paper: first, that a hump-shaped relationship exist between per capita income and deforestation; second, rural population density shifts this relationship upward in Africa. For Africa the turning point of the hump-shape is $4,760, and for Latin America $5,420. For most the observations of Cropper and Griffiths (1994) fall to the left of the peak, the authors conclude that economic growth will clearly not solve the problem of deforestation.

Meyer *et al.* (2003) examined the effects of economics, institutional and social capital variables on deforestation across 117 countries. The dependent variable is the rate of deforestation from 1990 to 2000. The economic regressors are PPP weighted GDP per capita, its square, forest product exports and agricultural output; the institutional regressors include size of government, the freedom to use alternative currencies, legal structure and property rights and the freedom of exchange in capital and financial markets. The control of corruption index and literacy are social capital regressors. While proportion of rural population is included as other regressor. Two OLS regression models are estimated. In the first one, the deforestation was regressed against only GDP and GDP-squared. The negative sign on the per capita GDP and positive sign on GDP-squared underlie a U shaped curve instead of a traditional inverted-U. Meyer *et al.* (2003) explained this curve as: poor countries have high deforestation rates because forestation is used as a useful tool in development. The rates continuously decrease when other industries are developing. After certain point, the countries begin to afforest. The rate of forestation keep increasing until peaks at some $19,500 per capita, and after which rate declines to zero. In this sense, their research supports EKC. The second model, which includes other regressors, discloses a greater government involvement and freedom of financial markets may have positive effects on forest protection.

2.3 Empirical Literature Review — Latest Research

Compared with empirical studies in the early stage, the latest research pays more attention to the functional form and econometric properties of the data in the study. Giles and Mosk (2003), Harbaugh *et al*. (2000), and Perman and Stern (2003) are the examples.

Giles and Mosk (2003) examine a very long-run relationship between income and emissions of CH_4 in New Zealand over the period of 1895 to 1996. They apply standard parametric regression, nonparametric regression and nonlinear regression based on fuzzy clustering analysis. The results from different methods are not the same. Based on traditional quadratic and cubic functional forms and nonparametric kernel regression, Giles and Mosk find an inverted U curve with single maximum at the levels of $7,000 - $7,500. With "fuzzy regression" methods, they find an M shaped curve.

Harbaugh *et al* (2000) test the sensitivity of the pollution-income relationship to additional covariates, and changes in the nations, cities and years sampled. The pollutant is SO_2. The functional form is cubic in lagged values of GDP. The estimation results are highly sensitive to the choice of these variables and functional forms. The EKC hypothesis is rejected.

Perman and Stern (2003) is the first paper that raises the point that empirical work on EKC using time series or panel data should consider the issue of non-stationarity.[2] They carry out both individual time-series unit root tests by Dickey-Fuller (1973) and panel data tests by Levin and Lin (1993) and by Im *et al*. (2003) for SO_2 and GDP for 74 countries over a span of 31 years. They find that the null hypothesis of unit root could be rejected in only a fraction of all the countries no matter whether the data are transformed into logarithm or remained unchanged. Then applying Levin and Lin (1993) panel unit root tests, Perman and Stern find support for unit root in both variables. The further tests following Im *et al*. (2003) also confirm this conclusion.

Following tests of cointegration provide support for the hypothesis that there is cointegration between emissions per capita and income per capita for each country in the panel. Though the error correction model (ECM) produces an inverted U curve, the heteroscedasticity among the countries shows that the EKC is a problematic concept, at least in the case of sulfur emissions.

[2] The issue of non-stationary in the context of Kuznets Curve (inequality-income relationship) has been analyzed in Jacobsen and Giles (1998), who used time-series data from the United States.

Perman and Stern (2003) make an important contribution to the empirical EKC research, but there are a few issues worth mentioning about their analysis. The issue that needs to be mentioned here is about Levin and Lin's (LL for short thereafter) alternative hypothesis. It is more restrictive than that for the more recent panel unit root tests like that of Im *et al*. (2003) (IPS for short thereafter). Also, a Monte Carlo study undertaken by Im *et al*. show that for finite samples, their test exhibits better performance compared to LL's test. While Perman and Stern use IPS test as well, this test does not seem appropriate for their dataset that has 31 periods each for 73 countries. The asymptotic in IPS test requires that the time dimension T to go to infinity, followed by the unit dimension N to go to infinity, i.e. T and N go to infinity sequentially. This requirement is not met at all for Perman and Sterns' data.

2.4 Literature Review on CO_2 Emission-Economic Growth Relationship

Carbon dioxide (CO_2) is one of the gases in the atmosphere, being uniformly distributed over the earth's surface at a concentration of about 0.033% or 330 ppm. Carbon dioxide is released into the atmosphere when carbon-containing fossil fuels such as oil, natural gas and coal are burned. As a result of the increasing worldwide consumption of fossil fuels, the amount of CO_2 in the atmosphere has increased over the past century, now rising at a rate of about 1 ppm per year. Major changes in global climate could result from a continued increase in CO_2 concentrations. According to the International Panel on Climate Control (IPCC), CO_2 accounts for more than half of global warming.

Several econometric studies have estimated the relation between CO_2 emissions per capita and per capita GDP growth using cross-country, and often unbalanced, panel data. Shafik (1994), Holtz-Eakin and Selden (1995), Sengupta(1996), Taskin and Zaim (2000), and Dijkgraaf and Vollebergh (2001) are examples of such research.

Most of the literature on CO_2 employs data from *Global, Regional, and National Fossil Fuel CO_2 Emissions* dataset created by the Carbon Dioxide Information Analysis Center of Oak Ridge National Laboratory. The pollutant data are derived primarily from energy statistics published by the United Nations, using the methods of Marland and Rotty (1984). The data indicate CO_2 emissions in each time period instead of the CO_2 stock in the air. However, the authors of various studies reach conflicting conclusions about the CO_2-GDP relationship from almost the same dataset.

CO_2 emissions are one of the eight pollutants analyzed by Shafik (1994). The data cover 1960 to 1989, and vary from 118 countries to 153. Shafik introduces four determinants of environmental quality into the model: (1) endowment such as climate and location, (2) per capita income, (3) exogenous factors such as technology, and (4) social policies. CO_2 emissions are regressed on various explanatory variables using simple log-linear, log-quadratic and log-cubic function forms. Shafik finds that per capita CO_2 emissions increase monotonically with income growth.

In contrast, Holtz-Eakin and Selden (1995) suggest a diminishing marginal effect of the emission of carbon dioxide as GDP per capita rises, but this effect is not significant. There are two other important conclusions drawn from their paper. One is that global carbon dioxide emissions grow at 1.8 percent per year for the foreseeable future, a result exogenous to the average output growth. The other is that the country-specific effect is important in the CO_2-GDP relationship. It could affect the interpretation of the econometric results. In their cross-sectional analysis, they find that industrialized countries yield higher emission–economic growth elasticities, while developing countries have lower elasticities. These results indicate a sensitivity to which countries are included in the modeling effort and reveal a potential for important differences in individual country behavior.

Sengupta (1996) models the CO_2-GDP relation for a mixed subset of 16 countries that includes both developed and developing countries. His models generate a much lower income turning point of $8,740 in PPP 1985 US dollars, but also find the tendency for positive emissions elasticities beyond $15,300. The N-shaped curve indicates that emissions decline over a mid-range of incomes before re-establishing an upward trend with GDP growth.

Taskin and Zaim (2000) also obtain their CO_2 emission data from the Carbon Dioxide Information Analysis Center. Following a suggestion by Holtz-Eakin and Selden (1995), they first construct environmental efficiency indexes for a group of high-income and low- and middle-income countries between the years 1975 and 1990 using a method proposed by Fare *et al*. (1989). Then they establish the link between environmental efficiency and per capita income using the Nadaraya-Watson kernel estimator where there is no requirement for the choice of a particular form for the conditional mean. Finally, by comparing the fitness of linear, quadratic and cubic models, they determine a cubic functional form for the relationship between environmental efficiency and GDP per capita, which has approximately a third-order polynomial shape indicating improving environmental performance at the initial phases of growth, which is followed by a phase of deterioration and then a further improvement once a critical level of per capita GDP is reached. This is actually another representation of the pollution-income relationship that mainly holds for countries at income levels of $5,000 and over.

Dijkgraaf and Vollebergh(2001) cast doubt on empirical EKC results based on a data set for OECD countries on CO_2 emissions for the period 1960-1997. They found that the crucial assumption of homogeneity of the pattern of the data across countries is problematic. Even within such a specific data set, where there is a wide overlap of observations for different countries at similar income levels, the graphs of carbon emission-economic growth relationships in the U.S. and Japan can easily show that a pool model for such a relationship is inconsistent. This argument is supported by the rejection of the null hypothesis of homogeneous country-specific slopes using LM tests. Regressions on the time series of each country indicate that the pollution-development relationships in some of the countries are of the inverted-U form, while others are monotonically increasing over time.

Until now, there has been no study on CO_2-growth relationship that has explained the issue of data non-stationarity. If the time series of CO_2 emission and GDP per capita are random walk, the residual from the estimation between them might also be integrated. Hence the regression is “spurious” and the interpretation to the model is meaningless. In this paper, I will exam the degree of integration of the panel data set. The tests on both individual series and panel set are applied and null of both stationarity and nonstationarity are tested.

SECTION 3: DATA AND EMPIRICAL STUDY

3.1 Data Description.

The pollutant we analyze in this paper is carbon dioxide. CO_2 emissions data also come from the *Global, Regional, and National Fossil Fuel CO_2 Emissions* by the Carbon Dioxide Information Analysis Center of Oak Ridge National Laboratory. The independent variable is *Gross Domestic Income*, which is expressed in 1996 Purchasing Power Parity (PPP) dollars. It is from Penn World Table 6.1 by the Center for International Comparisons at the University of Pennsylvania. Carbon dioxide emission and income levels are in logarithm so that the regression model provides the emission elasticities of income. The data set covers 50 countries for a period of 50 years, from 1951 to 1999. The list of the countries is provided in Appendix I, while the descriptive statistics are found in Table 1.

3.2 Empirical Study

3.2.1 Unit Root Tests to individual Series.

In contrast to cross-sectional data, time series data and panel data have some special properties, such as the value of a variable at certain period is affected by its lagged values. A shock in one period will affect all the following periods. The level of the effect is up to the parameters of the lagged terms. If the shock can be absorbed and eventually disappear, the series is called *stationary* and is denoted as *I(0)*; if it causes the series to explode, the series is *non-stationary.* In the simplest case, the series behaves as a *random walk,* which is denoted as *I(1)*. A model based on stationary data can measure a long-term relationship across variables. Granger and Newbold (1974) found that, when regressions are based on non-stationary data, estimation by OLS could lead to "spurious regressions", which are represented by high R^2 and a low Durbin-Watson statistics. Nelson and Plosser (1982) find that a great number of aggregate economic time series exhibit the characteristics of a random walk. However, if the linear combination of two or more non-stationary series is stationary, the series are said to be *co-integrated* and a long-term relationship can still be estimated by applying the series in levels. The formal definitions of *stationarity, unit root* and *order of integration* are provided in Appendix II.

We establish the order of integration of each series for each country y_{it} based on Dickey and Fuller (1979). We examine four different series for each country: CO_2 emission, GDP, square of GDP and cube of GDP. The standard specification of a simple autoregressive process of degree one (AR(1))is:

$$y_t = \rho y_{t-1} + x_t'\delta + \varepsilon_t \qquad (1)$$

where y_t is the series under consideration for a particular country, x_t is a vector of exogenous variables which may conclude constant, or a constant and trend, ε_t are assumed to be white noise. If $|\rho| \geq 1$,y_t is a nonstationary series and the variance of y_t increases with time and approaches infinity. If $|\rho| < 1$,y_t is a stationary series. The standard Dickey-Fuller test is carried out by estimating Equation (1) after subtracting y_{t-1} from both sides of the equation:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \varepsilon_t \qquad (2)$$

where $\alpha = \rho - 1$. The null and alternative hypotheses are then: H_0: $\alpha=0$ and H_a: $\alpha<0$. A t-ratio can be used to do the evaluation. However, Dickey and Fuller (1979) show that under the null hypothesis, this statistic does not follow the conventional Student's t-distribution. Simulated critical values are tabulated in the same paper and complemented by MacKinnon (1991, 1996).

The simple DF test is valid only if the series is an AR(1) process. If the series is correlated with higher order lags or is a moving average process of degree q (MA(q)), it can be converted into a AR process with infinite lags, and the assumption of white noise disturbances does not hold. The Augmented Dickey-Fuller (ADF) test introduces additional p-1 lagged terms to correct such bias.

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \sum_{j=1}^{p} \beta_j \Delta y_{t-j} + \varepsilon_t \qquad (3)$$

Fuller (1987) proves that the asymptotic distribution of the t-ratio for α is independent of the number of lagged differences included in the regression, which means the simulated critical values can be applied without any further modifications.

Two practical problems are raised in applying the ADF test. The first one is: What exogenous variables should be included? There are three choices: drift only, drift and trend, no drift and no trend. One approach would be to use the most general case and run a regression with both drift and trend since the other two cases are just special cases of such a specification. However, including irrelevant regressors in the regression will reduce the power of the test. A more general solution is to choose the exogenous variables that describe the data best under both the null and alternative hypotheses.

The second problem is specifying the level of augmentation *p*. One handy procedure is to assign a maximum augmented level p_{max}, then check the t-statistic of the coefficient of the last differenced term Δy_{t-j} is significant or not. If it is not significant, then this term is deleted, and we test the significance of the last differenced term in the new specification. If it is significant, then our level of augmentation is p_{max}.[3] Some econometrics programs such as SHAZAM and EViews can choose the lag length automatically. For example, in EViews, p lagged difference terms are added to a regression equation. The automatic selection methods choose p, which is less than the specified maximum, to minimize one of the information criteria.[4] The findings of the first procedure with drift, or drift and trend, as exogenous variables are listed in Table 2. From this table, we conclude the

[3] Another procedure---- ARIMA is suggested by Dolado *et al.* (1990) and Giles *et al.* (1992). The augmentation level is established by directly examining the autocorrelation and partial autocorrelations of the residuals of the ADF regression to ensure that they approximate white noise. If they do not, additional augmentation terms are added.
[4] The information criteria that are used in Eviews are Akaike (AIC), Schwarz (SIC), Hannan-Quinn (HQ), Modified AIC, Modified SIC and Modified HQ.

following: First, most of the series are a random walk, especially CO_2 emissions and GDP. This accords with prior studies of air pollution data. Second, some levels of integration of CO_2 data are sensitive to the model specification of the ADF regression. When a trend is included in the model, the t-ratio shows the series is stationary (nonstationary), but when the trend is excluded, the series is tested to be nonstationary (stationary). This requires a process of eliminating the time trend as an irrelevant exogenous variables, which is shown in Table 3. The third, Appendix Table 1 implies further tests on all I(1) series to determine if they are I(1) or I(2). In all cases the variables are found to be I(1).

As Kwiatkowski *et al*. (1991) points out, it is a well-known fact that the standard unit root tests fail to reject the null hypothesis of a unit root for many economic time series. The classical empirical example is presented in the influential article by Nelson and Plosser (1982). They failed to reject the hypothesis of a unit root in all 14 annual U.S. time series but one with both DF test and ADF test. Casting doubts on how informative these tests are about whether or not there is a random walk, DeJong and Whiteman (1991) applied Bayesian analysis on the same data set. They found only two of the series to have stochastic trends. Phillips (1991) used objective ignorance priors in extracting posteriors and found support for stochastic trends in five of the series. Some theoretical studies also confirm the argument. DeJong *et al*. (1989) provide evidence that the DF tests have low power against stable autoregressive alternatives with roots near unity, and Diebold and Rudebusch (1990) show that they also have low power against fractionally integrated alternatives. Therefore, the explanation for the common failure to reject a unit root is simply that the standard unit root tests are not very powerful against relevant alternatives.

These studies suggest that it would be useful to perform tests of the null hypothesis of stationarity as well as tests of the null hypothesis of a unit root. Park and Choi (1988) proposed a F test for “superfluous” deterministic trend variables; Rudebusch (1990) proposes DF test statistics both on trend-stationary and difference-stationary models. One popular testing procedure with stationary null hypothesis is proposed by Kwiatkowski *et al*. (1991), named as KPSS test. It avoids the problem of lacking of a plausible model in which the null of stationarity is naturally framed as a parametric restriction. The null hypothesis of KPSS test is trend stationarity which corresponds to the hypothesis that the variance of the random walk equals zero.

The KPSS statistic is based on the residuals from the OLS regression of y_t on the exogenous variables x_t: $y_y = x_t'\delta + u_t$. The Lagrange Multiplier statistic is be defined as

$$LM = \sum_{t=1}^{T} S(t)^2 \Big/ \hat{\sigma}^2 \qquad (4)$$

where $\hat{\sigma}^2$ is the estimate of the error variance and S(t) is a cumulative residual function: $S(t) = \sum_{i=1}^{t} \hat{u}_i$ based on the residuals $\hat{u}_t = y_t - x_t'\hat{\delta}$. Table 4 displays the KPSS statistics on the series of each country. The interesting finding in this table is that fewer series seem to be non-stationary. This is a confusing conclusion. Further study on the panel data as a whole is required.

3.2.2 Unit Root Tests on Panel Data

In the early 1990s, the econometric research came to have a wide use of panel data, which combines a cross-section of individual time-series. Such datasets yield valuable information and make the comparisons across units possible. However, the asymptotic properties of panel regression analysis have been derived under the assumption that the time-series data for each individual in the panel is weakly stationary, which conflicts with the fact that a wide range of macroeconomic variables present unit roots.

As the seminal contribution in this field, Levin and Lin (1993) developed asymptotic theory for panel data regression analysis when weak stationarity is violated by the presence of a unit root within each individual time-series.

The structure of the Levin and Lin analysis may be summarized in the following equation:

$$\Delta y_{i,t} = \alpha_i + \delta_i t + \theta_t + \rho_i y_{i,t-1} + \xi_{i,t}, \; i=1,2,...,N, \; t=1,2,..., T \qquad (5.1)$$

It allows for unit-specific effects (α_i) to control for country-specific heterogeneity, and time-specific effects (θ_t) to avoid the problem of serial correlation. The time-specific effects are taken into account in the panel unit root test by demeaning the data as $\tilde{y}_{it} = y_{it} - \bar{y}_t$ where $\bar{y}_t$ is the average over all countries at a particular point of time.

The null and alternative hypotheses are: H_0: $\rho_i=0$ for all i, against H_A: $\rho_i=\rho<0$ for all i.

Levin and Lin drew two conclusion from their analysis: first, this procedure yields higher power than standard unit-root tests based on individual time series; second, under the case when both the time-series and cross-section dimensions of the panel grow arbitrarily large ($T\to\infty$, $N\to\infty$), the panel regression estimators and t-statistics have limiting normal distributions; they converge at a faster rate as the number of time periods grows than as the number of individuals grows.

Some important empirical studies were based on Levin and Lin (1992). In 1996, Wu used panel data on real exchange rates between the US and eighteen OECD countries from 1974 to 1993.[5] With Levin and Lin's procedure, he found that the null hypothesis that real exchange rates during the post-Bretton Woods period contain a unit root could be decisively rejected. He argued that the failure to support the long-run PPP as reported by early researchers may result from the low power of standard univariate unit-root tests.

Further research by Im, Pssaran and Shin relaxed the restrictive assumption made by Levin and Lin (1992) that the values of ρ_i are homogeneous. Therefore the null and alternative hypotheses are modified into: H_0: $\rho_i=0$ for all i, against H_A:$\rho_i<0$, $i=1,2,...,N_1$, $\rho_i=0$, $i=N_1+1,N_1+2,...,N$.

[5] In fact, Wu used monthly data, quarterly data and annual data.

Im *et al*. (2003)[6] propose a likelihood test based on the average of DF statistics computed for each group in the panel, named t-bar test. The statistic is denoted as:

$$\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT} \qquad (6)$$

where t_{iT} is the DF statistic of the *i*th unit in the panel.

First, the authors assume that the errors of DF regressions are serially uncorrelated. Under a setting with T→∞, followed by N→∞, a standardized version of the $\bar{t}_{NT}$ statistic converges in probability to N(0,1) denoted as:

$$Z_{\bar{t}} = \frac{\sqrt{N}\{\bar{t}_{NT} - E(t_T)\}}{\sqrt{\mathrm{var}(t_T)}} \Rightarrow N(0,1) \qquad (7)$$

where $E(t_T)$ and $Var(t_T)$ are the mean and the variance of t_{iT} respectively.

Or, in a more complicated case, when T_i differs across groups, we have:

$$Z_{\bar{t}} = \frac{\sqrt{N}\{\bar{t}_{NT} - \frac{1}{N}\sum_{i=1}^{N} E(t_{Ti})\}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\mathrm{var}(t_{Ti})}} \Rightarrow N(0,1) \qquad (8)$$

The values of $E(t_T)$ and $var(t_T)$ for different T_s are listed in Im *et al* (2003, p.60).

A more general case in which the errors in Equation (1) are serially correlated with different serial correlation patterns across groups is considered in the second part of Im *et al* (2003). The ADF(p_i) regressions are introduced:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p_i} \rho_{ij}\Delta y_{i,t-j} + \varepsilon_{it}\ \text{, i=1,2,…,N, t=1,2,…,T} \qquad (9)$$

[6] This is a substantially revised version of the Department of Applied Economics, University of Cambridge, Working Papers Amalgamated Series No. 9526 (1997), University of Cambridge. Therefore, in some literature, it was cited as Im *et al* (1997).

t statistics of testing β_i=0 are now functions of nuisance parameters $\rho_i=(\rho_{i1}, \rho_{i2}, \ldots, \rho_{ip_i})'$ and p_i, that is, $t_{iT}=t_{iT}(p_i, \rho_i)$, and $\bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}(p_i, \rho_i)$. When T and N are sufficiently large it is possible to develop asymptotically valid tests. One of the practical alternatives is carrying out the standardization of the t-bar statistic using the means and variance of $t_{iT}(p_i, 0)$ evaluated under β_i=0. The standardized t-bar statistic under this assumption is:

$$W_{\bar{t}}(p,\rho) = \frac{\sqrt{N}\{\bar{t}_{NT} - \frac{1}{N}\sum_{i=1}^{N} E\left[t_{iT}(p_i,0)\middle|\beta_i = 0\right]\}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} \operatorname{var}\left[t_{iT}(p_i,0)\middle|\beta_i = 0\right]}} \Rightarrow N(0,1) \qquad (10)$$

The values of the mean and variance for different values of T and p obtained via stochastic simulations with 50,000 replications are given in Im *et al*. (2003, Table 3).

Table 5 lists the output of IPS tests on the 4 variables. The p_i of each series is for the individual ADF tests and shown in Table 2. The statistics of IPS tests show a support for the null hypothesis of non-stationarity.

IPS test is based on ADF test, taking unit root as null hypothesis. Given that in classical hypothesis testing, the null hypothesis is supported unless there is strong evidence against it, it is quite standard in unit root testing in individual time series case to use two different tests with two different null hypotheses to see if the results are robust. One has unit root as the null hypothesis (as ADF test) and one that has stationarity as the null hypothesis (as in KPSS test). Hadri (2000) proposes a unit root test on panel data whose null hypothesis is stationarity. His models are:

$$y_{it} = r_{it} + \varepsilon_{it} \qquad (11.1)$$

or

$$y_{it} = r_{it} + \beta_i t + \varepsilon_{it} \qquad (11.2)$$

where r_{it} is a random walk:

$$r_{it} = r_{i,t-1} + u_{it} \text{, and t=1,2,…, T and i=1,2,…,N,} \qquad (12)$$

both ε_{it} and u_{it} are identical independently distributed with E[ε_{it}]=0, E[$\varepsilon_{it}{}^2$]=$\sigma^2{}_\varepsilon$>0, E[u_{it}]=0, and E[$u_{it}{}^2$]=$\sigma^2{}_u \geq 0$. Substitute (12) into the models:

$$y_{it} = r_{i0} + e_{it} \qquad (13.1)$$

$$y_{it} = r_{i0} + \beta_i t + e_{it} \qquad (13.2)$$

where $e_{it} = \sum_{t=1}^{T} u_{it} + \varepsilon_{it}$. Hence, we have E[$e_{it}$]=0, and

$$E[e_{it}e_{js}] = \min(t,s)\sigma_u^2 + \sigma_\varepsilon^2 \quad \text{i=j, t=s}$$

$$= \min(t,s)\sigma_u^2 \quad \text{i=j, } t \neq s$$

$$=0 \quad i \neq j$$

If the series is stationary, then $\sigma_u^2 = 0$, otherwise, $\sigma_u^2 \neq 0$. Therefore, the null and alternative hypothesis of Hadri's test are: H_0: λ=0, against H_a: λ>0, where $\lambda = \sigma_u^2 / \sigma_\varepsilon^2$.

Hadri (2000) proves that for the null of stationary, the statistic of a panel has the following limiting distribution:

$$Z_\tau = \frac{\sqrt{N}(L\hat{M}_\tau - \frac{1}{6})}{\sqrt{\frac{1}{45}}} \Rightarrow N(0,1) \qquad (14.1)$$

where $L\hat{M}_x$ is the Lagrange Multiplier statistic of series x. For the null of trend stationary, the asymptotic distribution of the statistic is:

$$Z_{\tau} = \frac{\sqrt{N}(L\hat{M}_{\tau} - \frac{1}{15})}{\sqrt{\frac{11}{6300}}} \Rightarrow N(0,1) \qquad (14.2)$$

The result of Hadri's test for the series of CO_2 emission and GDI variables are given in Table 6. The results from this test are coinciding with that of IPS tests. Generally speaking, the data series we are working with are all non-stationary or I(1) and working with such data without further tests might lead to spurious regression.

Note that both IPS test and Hadri test use limits that involve $T \to \infty$ followed by $N \to \infty$, i.e. sequential asymptotic. If a panel dataset has a much larger time dimension than the unit dimension, this is justified (see, Hadri, 2000). Unfortunately, the dataset used here has N=T=50, but it is still better than Perman and Stern (2002) who used a smaller T than N and the IPS test.

SECTION 4. FURTHER RESEARCH

Based on the fact that the panel data sets of CO_2 emission and GDP per capita have unit root, cointegration analysis is suggested before doing regression. Cointegration analysis is used to test the validity of model, when the data are integrated time series. As mentioned before, if the residual from a regression of integrated variables is also integrated, the distribution of the regression parameters is highly non-standard, and the interpretation of the model is meaningless. However, if the integrated variables share the same stochastic trend, the residual will be stationary. In this case, the variables are called to be cointegrated. In such cases, the model is useful in interpreting the relationship between variables.

Because cointegration analysis is not the main part of this paper, here I will only briefly discuss tests for cointegration using panel data.

A popular test on the cointegration of time series data was proposed by Engle and Granger (1987). The two-step procedure using a linear model $y_t = \alpha + \gamma t + \beta x_t + \varepsilon_t$ is: First, estimate the model and generate the residual series $\hat{\varepsilon}_t$; then, construct "cointegrating regression augmented Dickey-Fuller" test (CRADF) as following:

$$\Delta\hat{\varepsilon}_t = \gamma\hat{\varepsilon}_{t-1} + \sum_{j=1}^{p} \beta_j \Delta\hat{\varepsilon}_{t-j} + v_t \qquad (15)$$

If we cannot reject the null hypothesis that γ equals zero against the alternative of γ is greater than zero, which means, $\hat{\varepsilon}_t = \alpha\hat{\varepsilon}_{t-1} + \sum_{j=1}^{p} \beta_j \Delta\hat{\varepsilon}_{t-j} + v_t$, and $\alpha<1$, then the series of $\hat{\varepsilon}_t$ is stationary. Hence, y_t and x_t are cointegrated, and further regression can be performed.

The same as unit root tests, cointegration tests to the individual series in a panel data set suffer from low power. In recent years, econometricians suggested some cointegration tests on dynamic panel. Also, such tests are divided into two catalogues by their hypotheses. One follows the idea of ADF test. The null hypothesis is the variables are cointegrated. Pedroni (1997a) describes in detail this method. The residual Pedroni procedure utilizes is generated by $y_{it} = \alpha_i + \gamma_i t + \beta_i x_{it} + \varepsilon_{it}$. This model permits heterogeneous slope coefficients, fixed effects and individual specific deterministic trends. Pedroni constructs seven panel cointegration statistics, four of "within dimension" and three of "between-dimension". For the within dimension tests, the null and alternative hypotheses are: $H_0 : \delta_i = 1$, for all i, H_A: $\delta_i=\delta<1$ for all i. For the between-dimension tests, the null and alternative are $H_0 : \delta_i = 1$, for all i, H_A: $\delta_i <1$ for all i. One statistic of each kind is based on ADF test. The rest are based on the unit root test suggested by Phillips and Perron (1988).

The other category of panel cointegration tests shares the same idea with KPSS test. The null hypothesis of such tests is that the series is not cointegrated. LM-test is used in the analysis. The details of such tests are in McCoskey & Kao (1998).

SECTION 5: CONCLUSION

Empirical work with time-series data needs to consider the properties of stationarity of data. If variables are characterized by a random walk, this may lead to "spurious regression". The interpretation based on such analysis will be meaningless. However, this problem was omitted by previous empirical literature on CO_2 emission-economic growth relationship.

This paper first applies unit root tests to the individual series in the data set. ADF tests the null hypothesis of non-stationarity against the alternative of stationarity. When the constant term is included as the only exogenous variable, 40 out of 50 countries have integrated series for CO_2, 44 out of 50 have integrated GDI per capita, – the integrated numbers of GDP per capita square and cube are both 44. When both constant and trend are included in the model, the numbers of the integrated series become 33, 44, 43 and 45, respectively. KPSS tests based on the null of stationarity report a similar output.

Unit root tests were applied to the panel data to increase the power of the tests. IPS tests hypothesize that all the series in the panel are a random walk; the alternative is that at least one of the series is stationary. The statistics to the data set strongly support the argument that we cannot reject the null hypothesis of stationarity. Hadri's tests are based on the null of stationarities of all the series. The large values of the statistics provide a resounding rejection of stationarity.

The non-stationarity of the panel data set has been proved. Further cointegration analysis is required to test if the residual is stationary or not. If cointegration among the variables is rejected, the conclusions of the previous literature on CO_2 emissions and economic growth would be refused. Future research is required to determine if this is truly the case.

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Figure 1. Spurious Regression

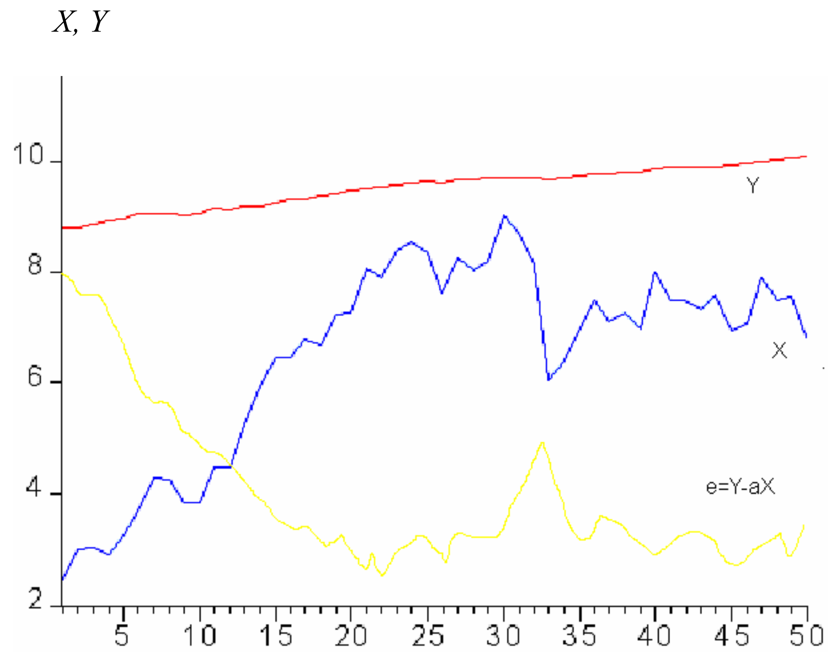

Table 1. Descriptive Statistics of Balanced Panel Data

Variables (in log)	Mean	Std. Dev	Min	Max
CO_2 Emission	-0.650	1.531	-4.605	2.393
GDP	8.582	0.958	6.096	10.663
GDI^2	73.321	1.613	-4.605	1.581
GDI^3	627.83	2.476	6.184	10.490

Table 2. Augmented Dickey-Fuller tests for order of integration

var	CO2		GDI		GDI^2		GDI^3		var	CO2		GDI		GDI^2		GDI^3	
#	c	c t	c	c t	c	c t	c	c t	#	c	c t	c	c t	c	c t	c	c t
1	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	26	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_1	4	5	0	0	8	8	8	8	P_{26}	0	0	8	8	0	0	1	1
2	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	27	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
P_2	0	0	6	6	6	6	6	6	P_{27}	8	8	0	0	1	1	4	4
3	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	28	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_3	7	5	8	8	8	8	8	8	P_{28}	7	7	0	0	0	0	0	0
4	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	29	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_4	0	0	8	8	0	0	0	0	P_{29}	3	3	4	4	4	4	4	4
5	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	30	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_5	0	6	0	0	6	6	6	6	P_{30}	7	7	8	8	8	8	8	8
6	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	31	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_6	5	5	2	2	2	2	2	2	P_{31}	6	2	0	0	7	7	8	8
7	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	32	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_7	1	6	1	1	6	6	6	6	P_{32}	0	0	0	0	2	2	2	2
8	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	33	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_8	0	0	4	4	4	4	4	4	P_{33}	0	0	0	0	0	0	0	0
9	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	34	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_9	7	4	6	6	6	6	6	6	P_{34}	1	2	4	4	4	4	4	4
10	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	35	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{10}	0	0	1	1	1	1	3	3	P_{35}	5	7	0	0	4	4	4	4
11	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	36	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{11}	0	0	1	1	1	1	1	1	P_{36}	0	0	1	1	1	1	1	1
12	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	37	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{12}	0	0	7	7	7	7	7	7	P_{37}	1	1	4	4	4	4	4	4
13	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	38	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{13}	0	4	7	7	7	7	2	2	P_{38}	0	0	2	2	4	4	4	4
14	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	39	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{14}	4	7	7	7	7	7	7	7	P_{39}	0	0	8	8	8	8	8	8
15	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	40	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{15}	0	0	8	8	8	8	8	8	P_{40}	8	8	0	0	1	1	1	1
16	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	41	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{16}	0	0	0	0	5	5	5	5	P_{41}	7	4	1	1	1	1	1	1
17	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	42	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{17}	0	0	2	2	2	2	2	2	P_{42}	0	4	1	1	4	4	4	4
18	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	43	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{18}	2	0	2	2	2	2	2	2	P_{43}	4	8	7	7	7	7	7	7
19	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	44	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{19}	6	6	6	6	6	6	6	6	P_{44}	7	7	7	7	7	7	7	7
20	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	45	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)
P_{20}	0	3	4	4	4	4	8	8	P_{45}	2	2	1	1	1	1	1	1
21	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	46	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{21}	0	0	6	6	6	6	6	6	P_{46}	4	8	0	0	0	0	5	5
22	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	47	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{22}	6	0	1	1	1	1	5	5	P_{47}	2	2	0	0	0	0	0	0
23	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	48	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
P_{23}	0	0	4	4	4	4	4	4	P_{48}	5	4	0	0	6	6	6	6
24	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	49	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
P_{24}	6	8	4	4	4	4	4	4	P_{49}	2	0	0	0	5	5	2	2
25	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	50	I(0)	I(1)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)
P_{25}	0	5	4	4	4	4	4	4	P_{50}	0	7	1	1	0	0	0	0

Table 3. Adjustment to Augmented Dickey-Fuller tests for Some CO_2 Emissions

CO2 emission country	exogenous variables		lag-terms	I(n)
3	c	t	5	I(0)
5	c	t	6	I(0)
20	c	t	3	I(1)
22	c		6	I(1)
24	c	t	8	I(0)
25	c	t	5	I(0)
27			8	I(0)
35		t	8	I(1)
37	c	t	1	I(0)
45	c	t	2	I(0)
46	c	t	8	I(0)
50			7	I(1)

Table 4. Augmented Dickey-Fuller tests for order of integration

var	CO2		GDI		GDI^2		GDI^3		var	CO2		GDI		GDI^2		GDI^3	
#	c	c t	c	c t	c	c t	c	c t	#	c	c t	c	c t	c	c t	c	c t
1	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	26	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
2	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	27	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
3	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	28	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
4	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)	29	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
5	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	30	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
6	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	31	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
7	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	32	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
8	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	33	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
9	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	34	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
10	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	35	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
11	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	36	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
12	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	37	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
13	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	38	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
14	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	39	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
15	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	40	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
16	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	41	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
17	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	42	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
18	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	43	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
19	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	44	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
20	I(0)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	45	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)
21	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	46	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
22	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	47	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
23	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	48	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
24	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	49	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(1)
25	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	50	I(0)	I(1)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)

Table 5. IPS Tests to the Panel Data

Exogenous variables	CO_2 emission	GDI	GDI^2	GDI^3
C	1.576	2.432	3.241	1.198
C,T	-0.235	1.937	-0.095	2.257
Conclusion	Cannot reject H0	Cannot reject H0	Cannot reject H0	Cannot reject H0

Table 6. Hadri's Tests to the Panel Data

Exogenous variables	CO_2 emission	GDI	GDI^2	GDI^3
C	530.61	618.23	627.00	634.81
C,T	137.78	140.54	137.83	133.86
Conclusion	Reject H0	Reject H0	Reject H0	Reject H0

Appendix I. The List of the Countries

Argentina	France	Mexico	Sri Lanka
Australia	Guatemala	Morocco	Switzerland
Belgium	Guyana	Netherlands	Thailand
Bolivia	Honduras	New Zealand	Turkey
Brazil	Iceland	Nicaragua	Uganda
Canada	India	Nigeria	United Kindom
Colombia	Ireland	Norway	USA
Costa Rica	Israel	Paraguay	Uruguay
Denmark	Italy	Peru	Venezuela
Egypt	Japan	Philippines	Panama
El Salvador	Kenya	Portugal	Spain
Ethiopia	Luxembourg	South Africa	
Finland	Mauritius	Trinidad and Tobago	

Appendix II. Some Time Series Definitions:

A. Stationary

A time series $\{y_t\}$ is "weakly stationary", or "covariance stationary" if the mean and variance of it are constant over time and the covariance of any sub-series of the original series are function of the difference between the two time points we choose the sub-series instead of the exact places of the points themselves.

B. Order of Integration

A series is said to be *integrated of order d* or *I(d)* if after being differenced d times it becomes stationary.

C. Cointegration

Suppose $\{x_t\}$, $\{y_t\}$ are both *I(d)* If there exists a linear combination, $z_t = ax_t + by_t$ which is *I(d-c)*; c>0, then $\{x_t\}$and$\{y_t\}$ are said to be "cointegrated.

Appendix Table 1. Augmented Dickey-Fuller tests for order of integration I(2)

var	CO_2		GDI		GDI^2		GDI^3		var	CO_2		GDI		GDI^2		GDI^3	
#	c	c t	c	c t	c	c t	c	c t	#	c	c t	c	c t	c	c t	c	c t
1	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	26	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{1}	3	3	1	1	1	1	5	5	P_{26}	0	1	7	7	0	0	0	0
2	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	27	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{2}	0	0	5	5	5	5	5	5	P_{27}	0	0	0	0	3	3	3	3
3	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	28	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{3}	4	6	7	7	7	7	7	7	P_{28}	8	6	0	0	0	0	0	0
4	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	29	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{4}	7	7	7	7	0	0	0	0	P_{29}	2	2	7	7	3	3	3	3
5	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	30	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{5}	0	0	0	0	5	5	8	8	P_{30}	0	6	7	7	7	7	7	7
6	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	31	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
P_{6}	4	8	1	1	1	1	1	1	P_{31}	1	1	8	8	8	8	8	8
7	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	32	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{7}	0	0	0	0	0	0	0	0	P_{32}	0	1	0	0	1	1	1	1
8	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	33	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{8}	0	0	3	3	3	3	8	8	P_{33}	0	0	0	0	0	0	0	0
9	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	34	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)
P_{9}	3	6	0	0	8	8	8	8	P_{34}	0	0	6	6	8	8	8	8
10	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	35	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{10}	8	8	0	0	0	0	1	1	P_{35}	6	7	1	1	3	3	3	3
11	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	36	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{11}	0	0	0	0	0	0	0	0	P_{36}	0	0	0	0	0	0	0	0
12	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	37	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)
P_{12}	1	1	6	6	6	6	6	6	P_{37}	0	0	6	6	8	8	8	8
13	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	38	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{13}	5	3	6	6	6	6	1	1	P_{38}	0	0	4	4	3	3	3	3
14	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	39	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{14}	6	3	6	6	6	6	6	6	P_{39}	0	0	7	7	7	7	7	7
15	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	40	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{15}	0	0	7	7	7	7	8	8	P_{40}	8	7	0	0	0	0	0	0
16	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	41	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{16}	1	1	0	0	0	0	4	4	P_{41}	6	3	6	6	6	6	6	6
17	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	42	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{17}	0	0	1	1	1	1	0	0	P_{42}	7	0	0	0	3	3	3	3
18	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	43	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{18}	1	1	1	1	1	1	1	1	P_{43}	3	3	6	6	6	6	6	6
19	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	44	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{19}	2	0	5	5	5	5	5	5	P_{44}	6	6	6	6	6	6	6	6
20	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	45	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{20}	2	6	0	0	6	6	6	6	P_{45}	0	0	0	0	0	0	1	1
21	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	46	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{21}	0	0	5	5	5	5	5	5	P_{46}	3	3	0	0	0	0	0	0
22	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	47	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{22}	5	0	0	0	0	0	4	4	P_{47}	0	0	0	0	0	0	0	0
23	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	48	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{23}	0	4	1	1	3	3	7	7	P_{48}	4	4	0	0	7	7	7	7
24	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	49	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{24}	2	2	3	3	3	3	3	3	P_{49}	1	1	0	0	0	0	0	0
25	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	50	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
P_{25}	0	0	3	3	3	3	3	3	P_{50}	4	4	7	7	7	7	7	7