Is the Economic Growth in the United States Influenced by Its Fossil Fuel-based Carbon Dioxide Emissions?

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Abstract

For the first time in the scientific literature, this research establishes empirical evidence for the existence of a causal relationship among fossil fuel-based carbon dioxide (CO_2) emissions in the United States (US), her gross domestic product (GDP) and world crude price. Estimated long-run income elasticity of CO_2 emissions is as high as 3.2% in the US. A strong bi-directional long-run causality is found between CO_2 emissions and GDP. Short-run causality runs from crude price to CO_2 emissions to GDP. Monte Carlo stochastic simulations of the model developed reveal even a small increase in the reference real GDP growth rate causes considerable increase in the future CO_2 emissions in the US. Results of this study therefore suggest urgent policy actions are imperative in the US to decouple the strong causal relationship existing between her CO_2 emissions and GDP, and to ensure sustainable economical development in the US.

Keywords: Carbon dioxide emissions, Cointegration, Crude oil price, Granger causality, GDP, United States, Monte Carlo stochastic simulations

1. Introduction

A century after the pioneering work of the influence of atmospheric carbon dioxide (CO_2) concentration upon global surface temperature (Arrhenius, 1896), the Intergovernmental Panel on Climate Change (IPCC, 1996) concluded that fossil fuel use was responsible for significant increase in atmospheric concentrations of greenhouse gases (GHG), inclusive of CO_2. IPCC (2007) states that average global surface temperature is likely to rise 1.1 to 6.4℃ during this century which has the potential to cause irreversible impact on ecosystems. With the intention of stabilizing atmospheric GHGs at levels that would slow down climate change, on 11th December 1997, world leaders adopted the Kyoto Protocol. In November 1998, the United States (US) signed the Kyoto Protocol which required the US and other economically developed countries to reduce their GHG emissions from 1990 levels by specified amounts during 2008 to 2012. In March 2001, the US announced that it would not ratify the Protocol.

In high income economies, such as the US, service sector dominates over manufacturing sector and changes in electricity-mix take place (Aldy, 2005). These factors together with technological progress have led to the popular concept that environmental pollution, inclusive of GHG emissions, in a country might decrease with income once the country surpasses a threshold income (Beckerman, 1992), which is known as the Environmental Kuznets Curve (EKC) hypothesis (Grossman & Krueger, 1991; Holtz-Eakin & Selden, 1995; Shafik & Bandyopadhyay, 1992). In case of GHG emissions complying with the EKC hypothesis, emission reductions similar to those suggested by the Kyoto Protocol would have been welcomed as achievable by economically developed countries, and as plausible by economically developing countries. The reality was the opposite. Adhering to the provisions of the Kyoto Protocol was seen as incompatible with achieving economic growth (Commonwealth of Australia, 2003; US Congress, 1997).

A recent inventory of GHG emissions and sinks in the US, published by the US Environmental Protection Agency (US EPA, 2010), states CO_2 emission from fossil fuel combustion has grown from 77% of total global warming potential-weighted emissions in 1990 to 80% in 2008, experiencing an 18% total increase over the last two decades. This increasing trend in emissions is attributed to the generally growing domestic economy, energy price fluctuations, and technological changes (US EPA, 2010).

This paper investigates into the existence or the absence of a causal relationship among fossil-fuel based CO_2 emissions in the US, her economic growth proxied by real gross domestic product (GDP), and energy price proxied by world crude oil real price. A time trend term is included in the long-run model to represent technological progress and other fossil fuel-based CO_2 emissions reduction strategies at work over time. Cointegration analysis, carried out in this study with annual data spanning the period 1950-2007, provides evidences for the existence of statistically significant long-run equilibrium relationship and a conditional equilibrium correction model (ECM).

Cointegration testing methodology used in this study is the autoregressive distributed lag (ARDL) bounds testing approach to cointegration (Pesaran et al., 2001). Even though ARDL approach requires no pre-testing to identify the order of integration of the time series considered, asymptotic (Pesaran et al., 2001) and finite-sample (Narayan, 2005) critical value bounds are valid for series with order of integration not exceeding unity. It is therefore, the time series data used are tested for unit roots using a recently developed nonlinear unit root test in the presence of a single structural break (Popp, 2008), and a linear test in the presence of two structural breaks (Narayan & Popp, 2010).

Since the above tests establish that CO_2 emissions, real GDP, and crude real price are $I(1)$ series, and that they are cointegrated, direction of Granger causality among them are examined using the error-correction based Granger causality tests (Acaravci & Ozturk, 2010). Granger causality results have immediate policy implications. For instance, if CO_2 emission Granger causes GDP then reduction in emissions in the US could harm her economy. On the other hand, if GDP Granger causes CO_2 emission then CO_2 emission reduction is possible in the US without harming her economic growth.

Forecasting is undertaken in cointegration studies (Amarawickrama & Hunt, 2008) by estimating future values of the dependent variable using the ECM developed for several different potential future scenarios of explanatory variables predicted in relevant official sources (Akashi et al., 2011; Amarawickrama & Hunt, 2008). In this study, Monte Carlo stochastic simulation (Mooney, 1997) of the ECM is used in forecasting CO_2 emissions since this technique has the power to convert the uncertainties in the future GDP growth rate of US and world crude price growth rate into probability distributions over the future CO_2 emissions in the US.

A brief review on the research literature on CO_2 emission–economic growth nexus for the US is given in Section 2, data used are presented along with model rationale in Section 3, a brief account of the econometric methodologies used is given in Section 4, and empirical results and discussion in Section 5. The potential use of the model in CO_2 emissions-economic growth related policy formulations in the US is discussed in Section 6, and Section 7 concludes.

2. Literature Review

Past research studies on CO_2 emission-economic growth nexus focused primarily upon the said relationship's ability to describe an EKC model. While Shafik and Bandyopadhyay (1992) and Shafik (1994) found CO_2 emissions per capita to increase with rising per capita income within the sample periods studied, Dijkgraaf and Vollebergh (1998) and Schmalensee et al. (1998) reported EKC-type relationships for CO_2 emissions-income nexus. Carrying out a comprehensive survey of empirical evidence and possible causes of EKCs describing pollution-income nexus, Lieb (2003) concluded that emission-income relationship monotonically rises for global pollutants, such as CO_2. Perman and Stern (2003) altogether negated the existence of EKC on the ground most of the EKC literature was devoid of testing for stochastic trends in the time series data used, and for spurious correlations of the models developed.

Testing the time series concerned for stationarity and cointegration was first introduced to the emissions-income research literature by Friedl and Getzner (2003) who found cointegration between Austrian yearly emissions and income time series during 1960-1999. Aldy (2005) tested for cointegration among emissions, income, and income-squared state-specific time series for the US using state-level yearly data spanning 1960-1999. Aldy found evidence for cointegration in 8 of the 48 states for production-based CO_2 emissions, and in 7 states for consumption-based CO_2 emissions. Dinda and Coondoo (2006) carried out a panel data-based cointegration analysis for 88 countries with annual data in the range of 1960-1990. Their results showed the null hypotheses of no cointegration between per capita CO_2 emission and per capita GDP could not be rejected for country groups such as North America, South America, Asia and Oceania. Therefore, they concluded long-run causality among the variables concerned was not probable for these country groups that included the US.

Arguing that countries in a group need not have similar economic dynamics, Soytas et al. (2007) investigated, for the US, Granger causality relationships among CO_2 emissions, real GDP, energy consumption, labour, and investment in fixed capital using annual data during 1960-2004. Using Toda and Yamamoto (1995) procedure, they found no causality between real GDP and CO_2 emissions and concluded that the US could reduce their carbon emissions without harming her economic growth. Causal relationship among CO_2 emissions, economic growth and energy consumption has also been investigated for China (Zhang & Cheng, 2009), five OPEC countries (Sari & Soytas, 2009), Turkey (Halicioglu, 2009), India (Ghosh, 2010), BRIC countries (Pao & Tsai, 2010), and for 19 European countries (Acaravci & Ozturk, 2010) among others. Conclusions reached in these studies varied from one country to another.

None of the above studies used energy price as an explanatory variable despite the local peaks experienced by CO_2 emissions in the US in 1973 and in 1979 during the oil shock decade. It was Unruh and Moomaw (1998) first showed, using phase diagrams, that per capita CO_2 emission's trajectories of the US and another 15 high income economies reached their respective peaks during the oil shock decade. In modelling both short-term and long-term dynamics of emissions in Sweden since 1870, Lindmark (2002) utilized a structural time series model with stochastic components having GDP and fuel prices as explanatory variables. Lindmark concluded that a combination of nuclear power, low economic growth, and increasing fuel prices had caused reduction in CO_2 emissions since early 1970s in Sweden.

In modelling CO_2 emissions in Austria since 1960, Friedl and Getzner (2003) pointed out that the sag in the N-shape (cubic) Austrian emissions versus income profile was caused by stringent environmental policies that came into effect following the oil shock decade. They also added that the upward trend found in the Austrian emissions in 1990s and in early 2000s could be explained as a 'recovery-effect' because the impact of the oil shock decade could have been much reduced in the 1990s and after.

Lanne and Liski (2004), working with data for the period 1870-1998 for 16 'early developed' countries, inclusive of the US, observed that the downward sloping trends in per capita CO_2 emissions caused by the oil shock decade were not stable, except for United Kingdom and Sweden. They used the additive outlier modelling approach which assumes structural changes in emissions trajectories being the results of sudden breaks in the trajectories caused by external shocks.

Huntington (2005) found variations in fuel prices during 1890-1998 to have statistically insignificant impact upon CO_2 emissions per capita in the US. He used econometric techniques fit for stationary time series, and concluded that 1% growth in real GDP per capita caused 0.9% growth in CO_2 emissions per capita when holding technological progress, proxied by time trend, constant.

Shanthini and Perera (2007) exposed the role of crude real price fluctuations in accounting for structural changes in CO_2 emissions versus income profiles of 17 high-income economies. They used a set of year-group dummy variables, the choice of which was solely guided by world crude real price fluctuations. A predictive model for Australia's per capita CO_2 emissions with per capita real GDP and world crude real price as explanatory variables was developed by Shanthini and Perera (2010) who used the ARDL bounds testing approach to cointegration for the first time to study the emissions-income-crude price nexus of a nation. Their study showed that world crude real price variations had very little influence on the emission-income nexus of Australia, which they attributed to Australia's possession of rich fossil fuel reserves. Similar analyses have been carried out in this study for the US.

3. Data and Model Rationale

Figure 1 shows the variations in annual CO_2 emissions stemming from fossil-fuel burning, cement manufacture and gas flaring in the US (Marland et al., 2010) against her annual real GDP (Bureau of Economic Analysis, 2010) during 1950-2007. CO_2 emissions data are in teragram (= 10^{12} g) of CO_2 equivalent, denoted by $TgCO_2$, and real GDP data are in billions of constant 2005$. Time period chosen for the analysis covers the period of intense CO_2 emissions growth and GDP growth in the US, which commenced in the 1950s (Figure 1). Choice of the end year as 2007 was dictated by CO_2 emissions data availability in the data source used.

As seen in Figure 1, CO_2 emissions in the US increased sharply with increasing real GDP till 1973, which was followed by a sharp reduction in emissions till 1975. Consequent recovery of the growth in emissions once again experienced a sharp reduction in 1979. Since 1982, CO_2 emissions increased with real GDP. However, it must be noted that the rate at which CO_2 emissions increased with real GDP since 1982 was much lower than the corresponding rate till 1973. It is therefore evident that statistical modelling of the relationship between CO_2 emissions and real GDP requires the use of suitably selected dummy variables or yet another explanatory variable that could account for the aforementioned discontinuities experienced by the CO_2 emission-real GDP relationship.

Figure 2 shows the annual variations in average world crude oil real price (British Petroleum, 2010) in constant 2009$ per barrel. World crude real price experienced very little fluctuations till 1973, then a sharp increase during 1973 to 1974, and another increase during 1978 to 1979. This decade of two major oil shocks was followed by a general decline in crude real price till 1986. Crude real price fluctuated about a near steady value till 2002 or so before setting up on an upward trend till 2007.

It is noteworthy that the decade of oil shocks, which is the 1970s, is nearly the same as the decade during which CO_2 emissions-real GDP relationship in the US experienced discontinuities (Figure 1). It is probable that abrupt increases experienced by crude real price during 1973 to 1974 and during 1978 to 1979 caused the breaks in emissions in 1973 and in 1979, respectively (Figure 1). It is therefore, I attempt to model CO_2 emissions in the US using real GDP and world crude real price as explanatory variables.

Inferring from the information presented above, I hypothesize, during the sample period 1950 to 2007, CO_2 emission time series of the US is strongly and positively correlated with her real GDP time series, and is negatively correlated with world crude oil real price. A time trend term is included in the model to explain any possible gradual reduction in emissions which could have been prompted by technological progress (Huntington, 2005) and other emissions reductions policies and strategies which have evolved during the past half century. I hypothesize that the coefficient of the time trend is therefore negative. Since I am interested in the temporal growths of the variables concerned, I use natural logarithms of the variables for model development. The hypothetical model therefore takes the following form:

$$C(t) = \omega_0 - \omega_t(t-1950) + \omega_G G(t) - \omega_O O(t)$$

where C, G and O represent the natural logarithms of fossil fuel-based CO_2 emissions in the US, real GDP in the US and world crude oil real price, respectively, t represents the time in year, and the Greek letters represent the coefficients to be determined.

4. Econometric Methodology

4.1 Order of Integration of the Time Series

The time series considered in this study exhibit discontinuities (Figure 1 and Figure 2), and therefore augmented Dickey-Fuller and other conventional tests may not correctly identify the order of integration (Perron, 1989). The series must therefore be tested for unit roots in the presence of structural breaks. To this effect, I employ the recently developed unit root testing methodologies of Popp (2008) and Narayan and Popp (2010). A distinctive feature in these two unit root tests is that they allow for structural break(s) under both the null hypotheses of the presence of unit root and the alternative of stationary series. They were also shown, via Monte Carlo simulations, to have stable power and to identify the true break date(s) very accurately even for small breaks (Narayan & Popp, 2010; 2012). Moreover, the unit root test of Popp (2008) is novel in the sense the coefficients of the test equation are nonlinearly related to each other. Owing to the novelty of these tests, they have been briefed in Appendix A of this paper.

4.2 ARDL Cointegration Analysis

ARDL bound testing approach to cointegration (Pesaran et al., 2001), in comparison with other cointegration methods (Engle & Granger, 1987; Johansen & Juselius, 1990), has the following advantageous features: (i) variables considered could be of different order of integration, (ii) efficient estimator even in small samples (iii) unbiased estimator of the long-run model even with endogenous regressors (iv) optimal order of lags of the series need not be the same, (v) current first-differenced regressors could be used as explanatory variables, and (iv) a single reduced form equation is used.

First step in the ARDL approach is to estimate the following unrestricted ECM.

$$\begin{aligned}\Delta C(t) = {} & \beta_0 + \beta_1 C(t-1) + \beta_2 G(t-1) + \beta_3 O(t-1) + \beta_4 (t-1950) + b_0 \Delta G(t) \\ & + d_0 \Delta O(t) + \sum_{i=1}^{m} a_i \Delta C(t\text{-}i) + \sum_{i=1}^{n} b_i \Delta G(t\text{-}i) + \sum_{i=1}^{p} d_i \Delta O(t\text{-}i) + \varepsilon(t)\end{aligned} \tag{1}$$

where β_0 is the intercept, β_1, β_2, β_3 and β_4 are the parameters of the long-run equilibrium ensemble, a_i, b_i, and d_i are the short-run dynamic parameters with m, n and p specifying the optimum lag lengths selected based on Akaike's Information Criterion (AIC) or Schwarz Criterion (SC), and $\varepsilon(t)$ is white noise.

Second step is to compute the F-statistic, at the selected optimum lag lengths, under the null hypothesis $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ (that is, no cointegration) against the alternative hypothesis that they are not. Computed F-statistic is then compared with the finite sample critical value bounds (Narayan, 2005). If it lies above the upper bound critical value then the null of no cointegration is rejected. If it lies below the lower bound critical value then the null cannot be rejected. If it lies within the bounds, then no conclusive decision could be drawn without knowing the order of integration of the regressors involved.

4.3 Long-run Equilibrium and Short –run Dynamics

If the null of no cointegration is rejected, then it is certain that the variables concerned are locked in a long-run equilibrium relationship, which is estimated starting from an ARDL model as the one given below:

$$ARDL(m,n,p):\quad C(t) = \mu_0 + \mu_t(t-1950) + \sum_{i=1}^{m}\gamma_i C(t\text{-}i) + \sum_{j=0}^{n}\tau_j G(t\text{-}j) + \sum_{k=0}^{p}\rho_k O(t\text{-}k) + ECT(t) \tag{2}$$

where μ_0 is the constant term, μ_t is the coefficient of the time trend, γ_i, τ_j and ρ_k are the coefficients of the first-differenced series, *m*, *n* and *p* denote the optimum lag lengths selected based on AIC/SC statistics, and *ECT(t)* are the serially uncorrelated residuals known as the equilibrium correction term.

ARDL(*m,n,p*) model is estimated using OLS procedure, and the coefficients of the corresponding long-run equilibrium relationship along with the standard errors and *t*-statistics are estimated using the Delta method (Pesaran & Shin, 1999). Conditional ECM corresponding to the chosen *ARDL*(*m,n,p*) model paves the way for estimating the short-run dynamic equation governing the variables *C*, *G* and *O*. In the conditional ECM, first difference of *C* is regressed on its lagged terms, current and lagged first differences of *G* and *O* and a one period lag of *ECT* using OLS regression (Pesaran et al., 2001).

Residuals of the conditional ECM are then tested for non-rejection of the null hypotheses of no residual serial correlation, no heteroskedasticity among the residuals, and normally distributed residuals. Stability of the estimated parameters are tested employing Ramsey regression specification error test (RESET), cumulative sum of recursive residuals (CUSUM) test and cumulative sum of squares of recursive residuals (CUSUMSQ) test.

4.4 Granger Causality Analysis

In case of cointegrated *I*(1) series, existence of Granger causality among them is tested using the following pair of equations (Acaravci & Ozturk, 2010; Narayan & Singh, 2007; Oxley & Greasley, 1998):

$$\begin{aligned}\begin{bmatrix}\Delta C(t)\\ \Delta G(t)\\ \Delta O(t)\end{bmatrix} &= \begin{bmatrix}\kappa_1\\ \kappa_2\\ \kappa_3\end{bmatrix} + \begin{bmatrix}\lambda_{11,1} & \lambda_{12,1} & \lambda_{13,1}\\ \lambda_{21,1} & \lambda_{22,1} & \lambda_{23,1}\\ \lambda_{31,1} & \lambda_{32,1} & \lambda_{33,1}\end{bmatrix}\begin{bmatrix}\Delta C(t-1)\\ \Delta G(t-1)\\ \Delta O(t-1)\end{bmatrix}\\ &+ \ldots + \begin{bmatrix}\lambda_{11,p} & \lambda_{12,p} & \lambda_{13,p}\\ \lambda_{21,p} & \lambda_{22,p} & \lambda_{23,p}\\ \lambda_{31,p} & \lambda_{32,p} & \lambda_{33,p}\end{bmatrix}\begin{bmatrix}\Delta C(t-p)\\ \Delta G(t-p)\\ \Delta O(t-p)\end{bmatrix} + \begin{bmatrix}\pi_1\\ \pi_2\\ \pi_3\end{bmatrix} ECT(t-1) + \begin{bmatrix}v_1\\ v_2\\ v_3\end{bmatrix}\end{aligned} \tag{3}$$

where κ_i (*i*=1,2,3) are the intercepts, $\lambda_{ij,k}$ (*i*=1,2,3; *j*=1,2,3; *k*=1,2,..*p*) are the coefficients of the lagged first-differenced variables, *p* is the optimum lag length selected based on AIC/SC, π_i (*i*=1,2,3) are the coefficients of the lagged *ECT*, and v_i (*i*=1,2,3) are the zero mean, constant variance, independently and normally distributed residuals.

Short-run (or weak) Granger causality tests are conducted by generating χ^2 statistic using the *F*-test of the lagged explanatory variable to establish rejection or non-rejection of the relevant null hypothesis, denoted by H_0. For example, ΔG Granger causes ΔC in the short-run if H_0: $\lambda_{12,1} = \lambda_{12,2} = \ldots = \lambda_{12,p} = 0$ is rejected. Long-run causality tests are conducted by assessing the significance of the *t*-statistics on the coefficients of the lagged *ECT*, which are π_i (*i*=1,2,3).

5. Results and Discussion

5.1 Order of Integration of the Time Series

Results obtained with unit root testing methodologies incorporating structural breaks (described in Appendix) are tabulated in Table 1 and Table 2. Since the primary interest is the unit root properties of the series tested, test statistics $t_{\hat{\alpha},NL}(\hat{T}_{B,1})$ and $t_{\hat{\alpha},L}(\hat{T}_{B,2})$, explained in Appendix A, tabulated in the tables are compared with the respective 5% critical values provided below the respective tables. Since none of the test statistics surpass the corresponding 5% critical values, null of unit root could not be rejected in any case studied, and therefore I concluded all three variables are *I*(1) series at 5% level of significance.

It is noteworthy to mention that all 12 models tested have highly significant coefficients of the break dummies, $\hat{\theta}_1$ and $\hat{\theta}_2$, explained in Appendix A. For crude real price, the first and the second break years are identified as 1973 and 1978, respectively, which correspond to the years of oil shocks, strongly supporting the model with two breaks in the levels (column 7 of Table 1). For real GDP, the first break year is identified as 1981 and the second break year as 1990 or 1991. For CO_2 emissions, M1 model identifies the first break year as 1973 and M2 model identifies it as 1981. The second break year is identified as 1975 by M1 and 1989 by M2. Statistical significance of the corresponding level and slope dummies, however, do not provide consistent evidence to conclude on the nature of structural break(s) in *G* and *C*.

5.2 Cointegration

As the next step, cointegration among *C*, *G* and *O* is tested using the ARDL bound testing procedure (Section 4.2). Both AIC and SC statistics select the optimum lag lengths in equation (1) as $m = 0$, $n = 3$ and $p = 0$ starting with the maximum lag length of 4 in each case which is adequate for annual data (Narayan & Smyth, 2005). Corresponding *F*-statistic is 10.107 for a sample size of 53 spanning 1955 to 2007. Since the upper bound critical value at 1% level of significance is 6.790 for a sample size of 50 and is 6.578 for a sample size of 55 (Narayan, 2005, p.1989), the null hypothesis $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ (no cointegration) is rejected at 1% level of significance when *C* is the dependent variable. When *C* and *G* are interchanged in equation (1), both AIC and SC select $m = 2$, $n = 1$ and $p = 1$, and the *F*-statistic is 5.453 for a sample size of 53. Since the upper bound critical values at 5% level of significance are 5.030 for a sample size of 50 and 4.955 for a sample size of 55 (Narayan, 2005, p.1989), null of no cointegration is rejected at 5% level of significance when *G* is the dependent variable.

5.3 Long-run Equilibrium

Rejection of the null of no cointegration assures the variables concerned are locked in a long-run equilibrium relationship. Starting from *ARDL*(*4,4,4*), the following long-run equilibrium relationship based on AIC statistic is estimated using the procedure outlined in Pesaran and Shin (1999):

$$ARDL(1,4,1)\text{:}\quad C(t) = -\underset{[-7.62]}{16.2359} - \underset{[-9.68]}{0.0899}(t-1950) + \underset{[11.28]}{3.2028}\,G(t) - \underset{[-2.82]}{0.0776}\,O(t) + ECT(t) \tag{4}$$

where *t*-statistics, given within the brackets, are computed using the Delta method (Pesaran & Shin, 1999), and their numerical values render statistical significance to the corresponding estimated parameters. SC statistic chooses *ARDL*(*1,3,0*) model, the coefficients and the *t*-statistics of which are very similar to those of equation (4).

Long-run equilibrium estimates in equation (4) show 1% growth in real GDP is associated with 3.2% growth in CO_2 emissions, when crude real price is frozen in time, and in the absence of progressive technological and policy-based CO_2 emissions reduction strategies, proxied by time trend. Decline in CO_2 emissions as a result of climbing crude real price, in the absence of technological and policy-based interventions, is realizable only if GDP growth is limited to a maximum of 2.4 (= 0.078/3.2) percent. These results also imply that technological and policy-wise interventions, under constant crude real price scenario, cause CO_2 emissions to decline only if real GDP grows at a rate less than 2.8 (= 0.09/3.2) percent.

5.4 Short-run Dynamics

Short-run dynamic equation is estimated from the conditional ECM corresponding to *ARDL*(*1,4,1*) using the OLS procedure. The general to specific procedure guided by minimising AIC statistic gave the following statistically significant conditional ECM:

$$\begin{aligned}\Delta C(t) = &-\underset{[-2.71]}{0.0224} - \underset{[-6.23]}{0.2529}\,ECT(t-1) + \underset{[8.65]}{0.9945}\,\Delta G(t) - \underset{[-2.30]}{0.3196}\,\Delta G(t-1)\\ &-\underset{[-3.71]}{0.4796}\,\Delta G(t-2) - \underset{[-2.12]}{0.2861}\,\Delta G(t-3)\end{aligned} \tag{5}$$

where *ECT(t-1)* is given by equation (4), and the statistical significance of the estimated parameters are testified by the corresponding *t*-statistics given within the brackets below the parameters concerned.

Equation (5) is estimated to have an adjusted R^2 of 69%, and a Durbin Watson statistic of 2.13. Estimated chi-squared statistics of Breusch-Godfrey serial correlation LM test, Jarque-Bera normality test, and ARCH heteroskedasticity test are $\chi^2_{SC}(4) =$ 5.34 [0.25], $\chi^2_{N}(2) =$ 3.92 [0.14], and $\chi^2_{H}(1) =$ 0.02 [0.89], respectively. P-values of the given chi-squared statistics, provided within the brackets, testify non-rejection of the null hypotheses of no residual serial correlation, no heteroskedasticity among the residuals, and normally distributed residuals.

Stability of the estimated parameters is assessed by the chi-squared statistic of RESET which is $\chi^2_{FF}(1) =$ 0.03, and the corresponding P-value is 0.86. Null of no misspecification in the model such as non-inclusion of all relevant variables is therefore rejected. Plots of CUSUM and CUSUMSQ test results, shown in Figure 3, confine themselves within the critical bounds of 5% significance. This implies the estimated coefficients of equation (5) are nearly constants from one sample period to the other, despite crude real price series experiencing two structural breaks within the sample period.

In interpreting equation (5), it must be noted that the coefficient of the equilibrium correction term *ECT(t-1)*, known as the adjustment parameter, not only has the expected negative sign implying negative feedback mechanism but also is highly significant (with the *t*-statistic of -6.23), which can be taken as further proof of the existence of a stable long-run equilibrium relationship (Banerjee et al., 1998). Numerical value of the adjustment parameter reveals that any deviation from the long-run equilibrium following a short-run disturbance is corrected by about 25% in a year. Coefficient of $\Delta G(t)$ reveals there is a 1:1 short-run dynamic relationship between GDP growth and CO_2 emission growth in a given year.

5.5 Granger Causality

Having estimated *ECT* by equation (4), long- and short-run Granger causalities are analyzed (Section 4.4). SC selected an optimum lag length of unity in equation (3) with the constant terms being replaced by the break dummies $DB_{73} = 1(t = 1974)$ and $DB_{81} = 1(t = 1982)$ to account for the structural breaks in the variables (Section 5.1). Other criterions such as AIC, Hannan-Quinn information criterion, and final prediction error selected the lag length to be six which is too large in comparison to the sample size of 57, and therefore not considered. *F*-test results of the lagged first-differenced explanatory variables, coefficients of the lagged *ECT*, and the corresponding P-values are tabulated in Table 3.

Table 3 shows, in the short-run, crude real price is significant at 5% level in the CO_2 emission equation whereas real GDP is not. In the real GDP equation, CO_2 emission is significant at 1% level in the short-run whereas crude real price is not. In the long-run, lagged *ECT* is significant at 1% level in the CO_2 emission equation and at 5% level in the real GDP equation. In both cases, coefficients of lagged *ECT* terms have the correct signs. In the crude real price equation, as anticipated, no term is statistically significant.

Empirical evidence, therefore, suggests, as could be visualized in Figure 4, in the short-run, Granger causality runs from world crude oil real price to CO_2 emissions to real GDP. Deviations from long-run equilibrium Granger cause changes in both CO_2 emissions and real GDP. That is, bi-directional long-run Granger causality runs between CO_2 emissions in the US and her GDP through the equilibrium correction term. It must be noted that Soytas et al. (2007) found no evidence for long-run causality (in any direction) between CO_2 emissions and real GDP in the US. Their approach however did not include crude real price as one of the explanatory variables.

6. Potential Use of the Model as a Policy Tool

It would be of considerable interest for the policy makers if reliable forecasts of future CO_2 emissions could be made using the ECM developed in this study. Forecast equation can be obtained (Amarawickrama & Hunt, 2008) by substituting the long-run equilibrium relationship (equation 4) in the conditional ECM (equation 5), and then by simplifying it as follows:

$$\begin{aligned} C(t) = 0.7471C(t-1) + 0.9945G(t) - 0.5041G(t-1) - 0.1600G(t-2) + 0.1935G(t-3) \\ + 0.2861G(t-4) - 0.0196O(t-1) - 0.0227(t-1951) - 4.1285 \end{aligned} \tag{6}$$

In-sample CO_2 emissions forecasted by dynamical simulation of the compound model are shown along with the actual CO_2 emissions in Figure 5. Dynamical simulation is carried out using the actual values of real GDP and crude real price, with the actual value of CO_2 emissions at 1953 as the initial input. As could be observed in Figure 5, compound model is able to closely predict the in-sample actual emissions, which is expected considering the stability of the estimated coefficients of the conditional ECM (Section 5.4).

Out-of sample forecasting of CO_2 emissions requires reliable real GDP and crude real price future projections be made available. Taking into account the uncertainties associated with such future projections, I use random number generators to provide future projections of real GDP and crude real price growth rates. Real GDP is generated using a triangular distribution having 1.8%, 2.4% and 3.0% as the minimum, reference and maximum real GDP growth rates till 2035. These rates are obtained from Annual Energy Outlook 2010 (AEO, 2010) published by the US Energy Information Administration (US EIA, 2010). World crude real price is generated using another triangular distribution with a reference growth rate of 1.1% (US EIA, 2010), and with minimum and maximum growth rates so chosen that they give about 50 and 200 constant 2009$ at 2035 (US EIA, 2010).

Results of 25 000 Monte Carlo simulations of equation (10), generated using MATLAB^{TM} package, are shown in Figure 6. The 50th percentile of Figure 6 gives the median emissions which could be taken as the most expected

CO_2 emissions forecast. The 2.5th and 97.5th percentiles bound the emissions range of 95% confidence level. Thus, when real GDP and crude real price are confined to the AEO2010-defined limits, it is most likely that the fossil fuel-based CO_2 emissions in the US will be below the 1990 emissions level beyond 2020, and will reach 3885 $TgCO_2$ in 2035. At 95% confidence level, it could be said that CO_2 emissions will be below the 1990 level beyond 2024, and that emissions will be confined to the range of 3560-4240 $TgCO_2$ in 2035.

In order to study the sensitivity of the CO_2 emissions forecast to the reference real GDP growth rate used in the simulations, I replaced the reference real GDP growth rate of 2.4 in the triangular distribution by 3.0. Results of 25 000 Monte Carlo simulations of equation (10), shown in Figure 6, reveal that it is most likely that the fossil fuel-based CO_2 emissions in the US will be below the 1990 emissions level beyond 2026, and will reach 4500 $TgCO_2$ in 2035. At 95% confidence level, it could be said that CO_2 emissions will be confined to the range of 4100-4950 $TgCO_2$ in 2035.

The above analyses in emission forecasts prove that increase in the reference real GDP growth rate has significant impact upon the future CO_2 emissions in the US for a business-as-usual scenario.

7. Conclusion

With the prime objective of learning from the fossil fuel-based CO_2 emissions-economic growth-world crude oil price nexus of a leading economy of the world, the underpinning nature of the relationship among them is investigated for United States (US) for the period 1950 to 2007.

Widely fluctuating nature of CO_2 emissions and crude real price called for the use of unit-root testing methodologies for series with structural break(s). Test results provide empirical evidence for all series being non-stationary. The relationship among the series considered is therefore analysed using a cointegration methodology.

ARDL bounds testing approach to cointegration provides empirical evidence for the existence of a long-run equilibrium relationship with 1% growth in real GDP being tied up with 3.2% growth in fossil fuel-based CO_2 emissions in the US, and 1% growth in crude real price being tied up with 0.08% decline in CO_2 emissions. The long-run model also captures the tendency for emissions growth to very gradually reduce with time.

The equilibrium correction model developed reveals any deviation from the long-run equilibrium relationship is corrected within a 4-year period. And, the short-run dynamics are such any change in the current annual growth in real GDP is tied up with equivalent change in the annual growth in emissions.

Granger causality analyses provide empirical evidence for short-run Granger causality running from world crude real price to CO_2 emissions to real GDP, and bi-directional long-run Granger causality running between CO_2 emissions in the US and her GDP. Policy implication of the existence of such bi-directional long-run Granger causality is that considerable reduction in fossil fuel-based CO_2 emissions in the US could hinder her economic growth. And, strong GDP growth in the US could be a cause for increase in fossil fuel-based CO_2 emissions.

Stability test results illustrated the model developed in this study is free of model misspecification such as non-inclusion of all relevant variables and the estimated coefficients are nearly constants from one sample period to the other. Therefore, the model developed is suitable for forecasting for a Business-as-usual scenario. Monte Carlo stochastic simulations of the compound model developed reveal, for a business-as-usual scenario, a small increase in the reference real GDP growth rate, such as from 2.5% to 3.0%, causes considerable increase in the future CO_2 emissions of the US.

The results of this study clearly demonstrate that it is the rate of economic growth and not the level of economy that decides on the CO_2 emission intensity of a high income economy, in contrast to the general belief CO_2 emission reduction is plausible once the economy is grown to satisfactory levels (the familiar EKC hypothesis). It is therefore evident that US needs to invest both on urgent policy-based solutions and long-term technological solutions to weaken the strong cointegrating relationship existing between CO_2 emissions and GDP.

References

Acaravci, A., & Ozturk, I. (2010). On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. *Energy*, 35, 5412-5420. http://dx.doi.org/10.1016/j.energy.2010.07.009

Akashi, O., Hanaoka, T., Matsuoka, Y., & Kainuma, M. (2011). A projection for global CO_2 emissions from the industrial sector through 2030 based on activity level and technology changes. *Energy,* 36, 1855-1867. http://dx.doi.org/10.1016/j.energy.2010.08.016

Aldy, J. E. (2005). An environmental Kuznets curve analysis of U.S. state-level carbon dioxide emissions. *The Journal of Environment & Development*, 14, 48-72. http://dx.doi.org/10.1177/1070496504273514

Amarawickrama, H. A., & Hunt, L. C. (2008). Electricity demand for Sri Lanka: a time series analysis. *Energy*, 33, 724-739. http://dx.doi.org/10.1016/j.energy.2007.12.008

Arrhenius, S. (1896). On the influence of carbonic acid in the air upon the temperature of the ground. *Philosophical Magazine and Journal of Science*, 41, 237-276. [Online] Available: http://www.rsc.org/images/Arrhenius1896_tcm18-173546.pdf

Banerjee, A., Dolado, J., & Mestre, R. (1998). Error-correction mechanism tests for cointegration in single-equation framework. *Journal of Time Series Analysis*, 19, 267-283. http://dx.doi.org/10.1111/1467-9892.00091

Beckerman, W. (1992). Economic growth and the environment: whose growth? whose environment? *World Development*, 20, 481-496. http://dx.doi.org/10.1016/0305-750X(92)90038-W

British Petroleum. (2011). Statistical review of world energy June 2011. [Online] Available: http://www.bp.com/statisticalreview (July 27, 2011).

Bureau of Economic Analysis. (2011). National economic accounts: current-Dollar and Real GDP updated on 25/06/2010. [Online] Available: http://www.bea.gov/national/xls/gdplev.xls (July 27, 2011).

Commonwealth of Australia. (2003). Kyoto Protocol ratification bill 2003 [No. 2]. [Online] Available: http://www.aph.gov.au/senate/committee/ecita_ctte/completed_inquiries/2002-04/kyoto/report/report.pdf (Sept 29, 2011).

Dijkgraaf, E., & Vollebergh, H. R. J. (1998). Growth and/or environment: is there a Kuznets Curve for carbon emissions? *Paper Presented at the 2nd biennial meeting of the European Society for Ecological Economics.* March 4-7, 1998. Geneva.

Dinda, S., & Coondoo, D. (2006). Income and emission: a panel data-based cointegration analysis. *Ecological Economics*, 57, 167-181. http://dx.doi.org/10.1016/j.ecolecon.2005.03.028

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55, 251-276. http://dx.doi.org/10.2307/1913236

Friedl, B., & Getzner, M. (2003). Determinants of CO_2 emissions in a small open economy. *Ecological Economics*, 45, 133-148. http://dx.doi.org/10.1016/S0921-8009(03)00008-9

Ghosh, S. (2010). Examining carbon emissions economic growth nexus for India: a multivariate cointegration approach. *Energy Policy*, 38, 3008-3014. http://dx.doi.org/10.1016/j.enpol.2010.01.040

Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American free trade agreement*. Princeton, N.J.: Woodrow Wilson School.

Halicioglu, F. (2009). An econometric study of CO_2 emissions, energy consumption, income and foreign trade in Turkey. *Energy Policy*, 37, 1156–1164. http://dx.doi.org/10.1016/j.enpol.2008.11.012

Holtz-Eakin, D., & Selden, T. M. (1995). Stoking the fires? CO_2 emissions and economic growth. *Journal of Public Economics*, 57, 85-101. http://dx.doi.org/10.1016/0047-2727(94)01449-X

Huntington, H. G. (2005). U.S. carbon emissions, technological progress and economic growth since 1870. *International Journal of Global Energy Issues*, 23, 292-306.

IPCC. (1996). IPCC Second assessment: climate change 1995. [Online] Available: http://www.ipcc.ch/publications_and_data/publications_and_data_reports.htm (Sept 29, 2011).

IPCC. (2007). Climate change 2007: synthesis report. [Online] Available: http://www.ipcc.ch/publications_and_data/publications_and_data_reports.htm (Sept 29, 2011).

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics.* 52, 169-210. http://dx.doi.org/10.1111/j.1468-0084.1990.mp52002003.x

Lanne, M., & Liski, M. (2004). Trends and breaks in per-capita carbon dioxide emissions, 1870-2028. *The Energy Journal*, 25, 41-65. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol25-No4-3

Lieb, C. M. (2003). The environmental Kuznets curve-a survey of the empirical evidence and of possible causes. *Discussion Paper Series*, No. 391. Department of Economics, University of Heidelberg. [Online] Available: http://www.uni-heidelberg.de/md/awi/forschung/dp391.pdf

Lindmark, M. (2002). An EKC-pattern in historical perspective: carbon dioxide emissions, technology, fuel prices and growth in Sweden 1870-1997. *Ecological Economics*, 42, 333-347. http://dx.doi.org/10.1016/S0921-8009(02)00108-8

Marland, G., Boden, T. A., & Andres, R. J. (2011). CDIAC: global, regional and national fossil fuel CO_2 emissions. [Online] Available: http://cdiac.ornl.gov/trends/emis/em_cont.html (July 27, 2011).

Mooney, C. Z. (1997). Monte Carlo simulation. *Sage University Paper series on Quantitative Applications in the Social Sciences.* Vol. 116. Thousand Oaks, California: Sage.

Narayan, P. K. (2005). The saving and investment nexus for China: evidence from cointegration tests. *Applied Economics*, 37, 1979-1990. http://dx.doi.org/10.1080/00036840500278103

Narayan, P. K., & Popp, S. (2012). A nonlinear approach to testing the unit root null hypothesis: an application to international health expenditures. *Applied Economics*, 44, 163-175. http://dx.doi.org/10.1080/00036846.2010.500276

Narayan, P. K., & Popp, S. (2010). A new unit root test with two structural breaks in level and slope at unknown time. *Journal of Applied Statistics*, 37, 1425-1438. http://dx.doi.org/10.1080/02664760903039883

Narayan, P. K., & Singh, B. (2007). The electricity consumption and GDP nexus for the Fiji islands. *Energy Economics*, 29, 1141-50. http://dx.doi.org/10.1016/j.eneco.2006.05.018

Narayan, P. K., & Smyth, R. (2005). The consensual norm on the high court of Australia: 1904-2001. *International Political Science Review*, 26, 147-68. http://dx.doi.org/10.1177/0192512105050379

Oxley, L., & Greasley, D. (1998). Vector autoregression, cointegration and causality: testing for cause of the British industrial revolution. *Applied Economics*, 30, 1387-1397. http://dx.doi.org/10.1080/000368498325002

Pao, H.-T., & Tsai, C.-M. (2010). CO_2 emissions, energy consumption, and economic growth in BRIC countries. *Energy Policy*, 38, 7850-7860. http://dx.doi.org/10.1016/j.enpol.2010.08.045

Perman, R., & Stern, D. I. (2003). Evidence from panel unit root and cointegration tests that the environmental Kuznets curve does not exist. *Australian Journal of Agricultural and Resource Economics*, 47, 325-347. http://dx.doi.org/10.1111/1467-8489.00216

Perron, P. (1989). The great crash, the oil price shock and the unit root hypothesis. *Econometrica*, 57, 1361-1401. http://dx.doi.org/10.2307/1913712

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. *Journal of Econometrics*, 80, 355-385. http://dx.doi.org/10.1016/S0304-4076(97)00049-3

Pesaran, H. M., & Shin, Y. (1999). Autoregressive distributed lag modelling approach to cointegration analysis. In S. Storm (ed.). *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium* (pp. 371-413). Cambridge: Cambridge University Press.

Pesaran, H. M., Shin. Y., & Smith, R. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16, 289-326. http://dx.doi.org/10.1002/jae.616

Popp, S. (2008). A nonlinear unit root test in the presence of an unknown break. *Ruhr Economic Paper No.* 45. http://dx.doi.org/10.2139/ssrn.1132782

Sari, R., & Soytas, U. (2009). Are global warming and economic growth compatible? Evidence from five OPEC countries? *Applied Energy*, 86, 1887-1893. http://dx.doi.org/10.1016/j.apenergy.2008.12.007

Schmalensee, R., Stoker, T. M., & Judson, R. A. (1998). World carbon dioxide emissions: 1950-2050. *Review of Economics and Statistics*, 80, 15-27. http://dx.doi.org/10.1162/003465398557294

Shafik, N. (1994). Economic development and environmental quality: an econometric analysis. *Oxford Economic Papers*, 46, 757-773. http://www.jstor.org/stable/i325761

Shafik, N., & Bandyopadhyay, S. (1992). Economic growth and environmental quality: time series and cross-country evidence. *Background paper for World Development Report 1992*. Washington, D.C: World Bank.

Shanthini, R., & Perera, K. (2007). Oil price fluctuation incorporated models for carbon dioxide emissions and energy consumption of high-income economies. *Ceylon Journal of Science: Physical Sciences*, 13, 45-59.

Shanthini, R., & Perera, K. (2010). Is there a cointegrating relationship between Australia's fossil-fuel based carbon dioxide emissions per capita and her GDP per capita? *International Journal of Oil, Gas and Coal Technology*, 3, 182-200. http://dx.doi.org/10.1504/IJOGCT.2010.033564

Soytas, U., Sari, R., & Ewing, B. T. (2007). Energy consumption, income, and carbon emissions in the United

States. *Ecological Economics*, 62, 482-489. http://dx.doi.org/10.1016/j.ecolecon.2006.07.009

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregression with possibly integrated processes. *Journal of Econometrics*, 66, 225-250. http://dx.doi.org/10.1016/0304-4076(94)01616-8

Unruh, G. C., & Moomaw, W. R. (1998). An alternate analysis of apparent EKC-type transitions. *Ecological Economics*, 25, 221-229. http://dx.doi.org/10.1016/S0921-8009(97)00182-1

US Congress. (1997). Byrd-Hagel resolution. Proceedings of the 105th Congress 1997: S. Res. 98: Report No. 105-54. [Online] Available: http://www.nationalcenter.org/KyotoSenate.html (Sept 29, 2011).

US EIA. (2010). Assumptions to the annual energy outlook 2010: with projections to 2035. April 2010. [Online] Available: http://www.eia.doe.gov/oiaf/aeo/assumption/pdf/0554(2010).pdf (Feb 15, 2011).

US EPA. (2010). *Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990-2008.* United States: Environmental Protection Agency (EPA 430-R-10-006). http://epa.gov/climatechange/emissions/downloads11/US-GHG-Inventory-2011-Complete_Report.pdf

Zhang, X. P., & Cheng, X. M. (2009). Energy consumption, carbon emissions, and economic growth in China. *Ecological Economics*, 68, 2706-2712. http://dx.doi.org/10.1016/j.ecolecon.2009.05.011

Table 1. Test statistics of unit root tests with structural break(s) in the level (model M1). Notations used are explained in Appendix A

Parameter and test statistic	C		G		O	
	$M1_{1B,L}$ [$M1_{1B,NL}$]	$M1_{2B,L}$	$M1_{1B,L}$ [$M1_{1B,NL}$]	$M1_{2B,L}$	$M1_{1B,L}$ [$M1_{1B,NL}$]	$M1_{2B,L}$
$k_{\max}$	15	15	15	15	15	20
k	0 [0]	0	8 [8]	0	6 [6]	18
$\hat{T}_{B,1}$	1973	1973	1981	1981	1973	1973
$\hat{T}_{B,2}$		1975		1990		1978
$\hat{\alpha}$	-0.0065	-0.0054	-0.1697	-0.2494	-0.2352	-2.3363
$t_{\hat{\alpha},NL}(\hat{T}_{B,1})$	[-0.145]		[-1.630]		[-2.389]	
$t_{\hat{\alpha},L}(\hat{T}_{B,2})$		-0.119		-2.499		-4.281
$\hat{\eta}_0$	0.069^{ns}	0.061^{ns}	1.3608*	1.9368**	0.5325*	5.702***
$\hat{\eta}_t$	0.0009^{ns}	0.0009^{ns}	0.0051^{ns}	0.0085**	0.0055^{ns}	0.0145***
$\hat{\theta}_1$	-0.072**	-0.073**	-0.072***	-0.058***	1.1375***	1.2735***
$\hat{\theta}_2$		0.088**		0.0412**		0.8459***
$\hat{\varsigma}_1$	-0.044***	-0.081***	0.0012^{ns}	-0.0026^{ns}	0.0868^{ns}	0.9145***
$\hat{\varsigma}_2$		0.035^{ns}		-0.0169^{ns}		1.0233**

Notes: *** and ** represent 1% and 5% significance levels, respectively, and ^{ns} represents non-significance even at 10% level. Results of the non-linear model (outlined in Appendix A) are given within the brackets. Critical values at 5% level of significance are -3.610 for $t_{\hat{\alpha},NL}(\hat{T}_{B,1})$ and -4.514 for $t_{\hat{\alpha},L}(\hat{T}_{B,2})$ for a sample size of 50, and are -3.498 and -4.316 for a sample size of 100. They are obtained from Table 3 of Popp (2008) and Table 3 of Narayan and Popp (2010), respectively.

Table 2. Test statistics of unit root tests with structural break(s) in the level and slope (model M2). Notations used are explained in Appendix A

Parameter and test statistic	*C*		*G*		*O*	
	$M2_{1B,L}$ [$M2_{1B,NL}$]	$M2_{2B,L}$	$M2_{1B,L}$ [$M2_{1B,NL}$]	$M2_{2B,L}$	$M2_{1B,L}$ [$M2_{1B,NL}$]	$M2_{2B,L}$
k_{max}	15	15	15	15	15	20
k	6 [6]	10	6 [8]	13	6 [5]	18
$\hat{T}_{B,1}$	1981	1981	1981	1981	1973	1973
$\hat{T}_{B,2}$		1989		1991		1978
$\hat{\alpha}$	-0.315	-1.318	-0.696	-1.6385	-0.2349	-2.4325
$t_{\hat{\alpha},NL}(\hat{T}_{B,1})$	[-0.717]		[-1.055]		[-2.399]	
$t_{\hat{\alpha},L}(\hat{T}_{B,2})$		-3.649		-2.147		-4.831
$\hat{\eta}_0$	2.439**	10.03***	5.246***	12.11**	0.525^{ns}	4.007**
$\hat{\eta}_t$	0.0078*	0.035***	0.026***	0.060*	0.0059^{ns}	0.107**
$\hat{\theta}_1$	-0.098***	-0.113***	-0.094***	-0.098***	1.134***	1.036***
$\hat{\theta}_2$		-0.073**		0.047**		1.029***
$\hat{\varsigma}_1$	-0.029^{ns}	-0.079*	-0.028*	-0.013^{ns}	0.084^{ns}	0.934**
$\hat{\varsigma}_2$		-0.108***		0.013^{ns}		1.308***
$\hat{\xi}_1$	-0.0050*	-0.019*	-0.004***	-0.015**	-0.0005^{ns}	-0.192^{ns}
$\hat{\xi}_2$		0.0010^{ns}		0.0059**		0.100^{ns}

Notes: Same as in Table 1 except for the critical values which are -4.168 for $t_{\hat{\alpha},NL}(\hat{T}_{B,1})$ and -5.181 for $t_{\hat{\alpha},L}(\hat{T}_{B,2})$ for a sample size of 50, and are -3.953 and -4.937 for a sample size of 100.

Table 3. Results of error-correction based Granger causality tests

Dependent variable	*F*-statistics of the explanatory variables			coefficients of
	$\Delta C(t)$	$\Delta G(t)$	$\Delta O(t)$	$ECT(t\text{-}1)$
$\Delta C(t)$	-	0.023	5.332**	-0.1129***
		(0.871)	(0.017)	(0.005)
$\Delta G(t)$	6.457***	-	2.043	-0.0828**
	(0.009)		(0.134)	(0.018)
$\Delta O(t)$	0.017	0.181		0.0263
	(0.888)	(0.652)		(0.929)

Notes: *** and ** represents 1% and 5% significance levels, respectively. P-values are provided within the parenthesis.

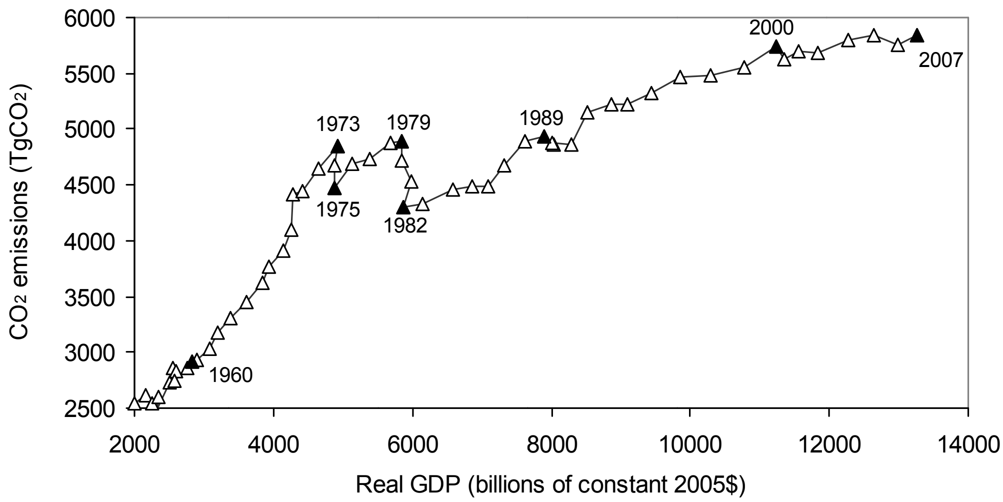

Figure 1. Annual fossil fuel-based CO_2 emissions in the United States against her annual real gross domestic product during 1950 to 2007

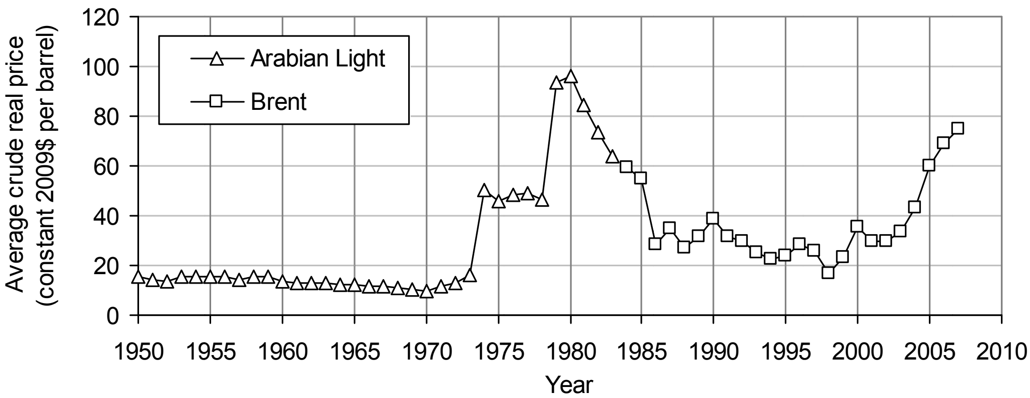

Figure 2. Annual average world crude oil real price during 1950 to 2007

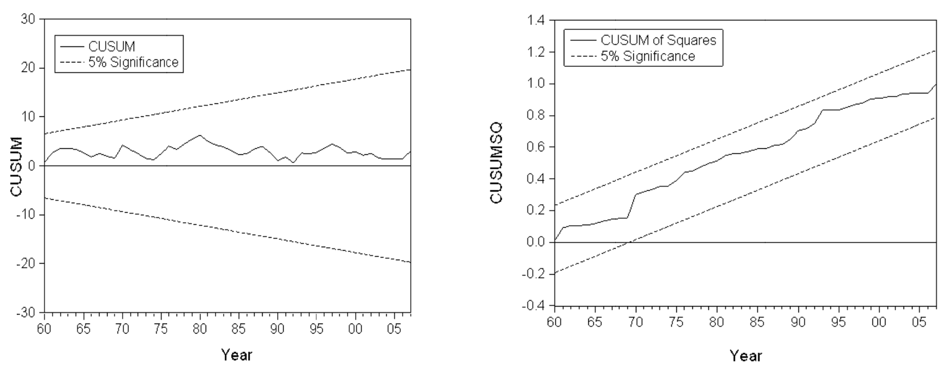

Figure 3. Cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares of recursive residuals (CUSUMSQ) of the ECM of equation (9)

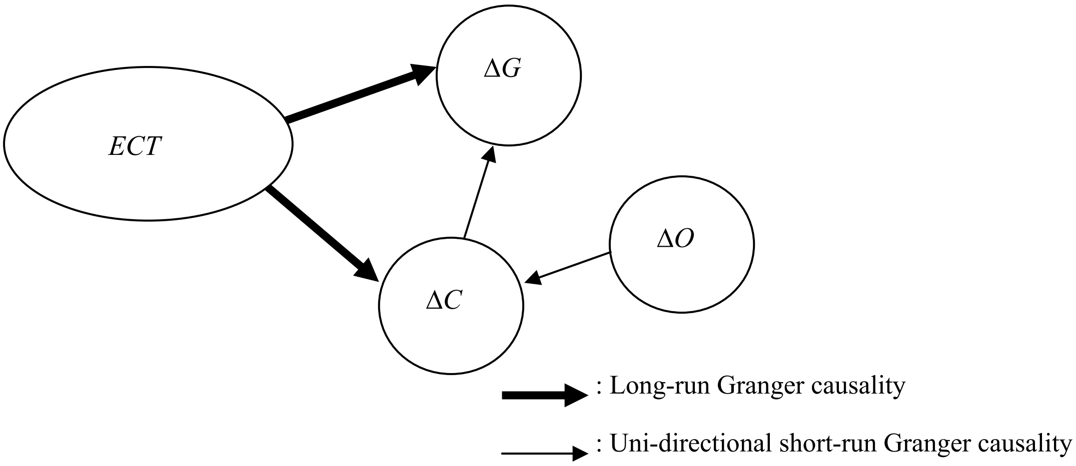

Figure 4. Granger causality dynamics. ΔC, ΔG and ΔO represent relative growths in CO_2 emissions, real GDP and world crude oil real price, and *ECT* represents deviation from the long-run equilibrium among the three variables at level

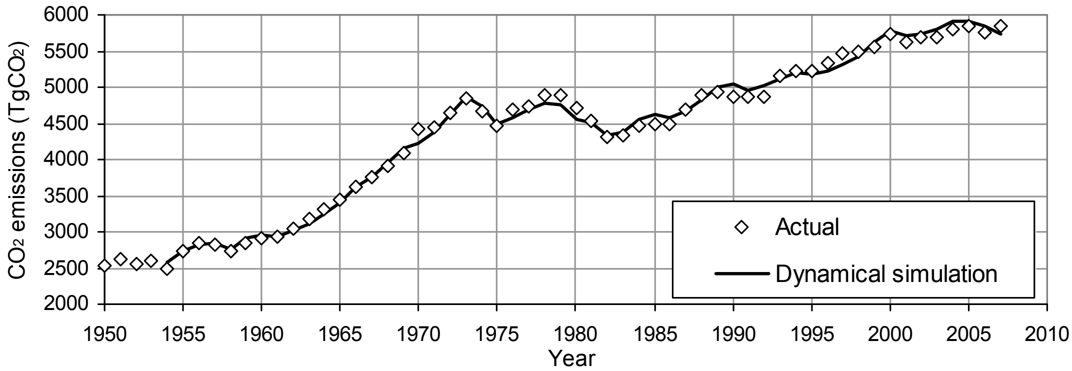

Figure 5. Dynamically simulated CO_2 emissions using equation (10) compared with the actual values

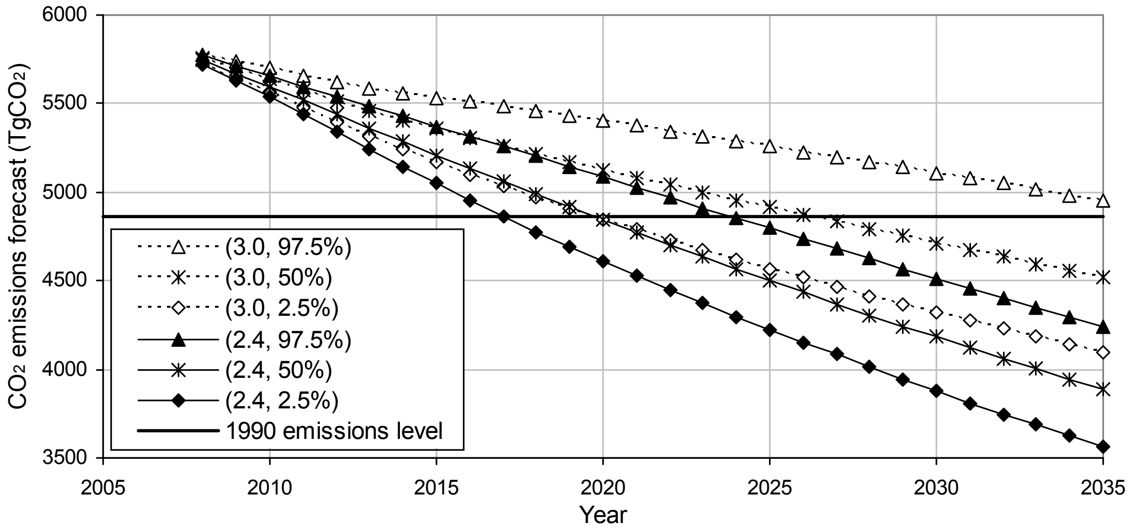

Figure 6. Percentiles (97.5%, 50% and 2.5%) of the CO_2 emissions forecast using 25 000 Monte Carlo simulations. First entry within the parentheses in the legend represents reference real GDP growth rate used and the second entry the percentile

Appendix A

The most general test equation underlying the unit root testing methodologies of Popp (2008) and Narayan and Popp (2010) for a trending series is as follows:

$$\begin{aligned}\Delta y(t) &= \alpha y(t-1) + \eta_0 + \eta_t t + \theta_1 DB_1(t) + \varsigma_1 DU_1(t-1) + \xi_1 DT_1(t-1) \\ &+ \theta_2 DB_2(t) + \varsigma_2 DU_2(t-1) + \xi_2 DT_2(t-1) + \sum_{j=1}^{k} \eta_j \Delta y(t-j) + e_t\end{aligned} \tag{A1}$$

where Δ is the first difference operator, y is the time series being tested, t is the time, $DB_i = 1(t = T_{B,i} + 1)$, i=1,2, are the break dummies, $T_{B,i}$, i=1,2, are the endogenously determined break years, $DU_i = 1(t > T_{B,i})$, i=1,2, are the intercept dummies, $DT_i = 1(t > T_{B,i})(t - T_{B,i})$, i=1,2, are the slope dummies, k is the lag length, $e_t \sim iid(o, \sigma_e^2)$, and the Greek letters represent the coefficients to be determined.

A time series is first tested for a single structural break using the following linear test equations Popp (2008):

$M1_{1B,L}$: Test equation for one break in the level of a trending series:

$$\text{Equation (A1) with } \xi_1 = 0;\ \theta_2 = 0;\ \varsigma_2 = 0;\ \xi_2 = 0 \tag{A2}$$

$M2_{1B,L}$: Test equation for one break in the level and slope of a trending series:

$$\text{Equation (A1) with } \theta_2 = 0;\ \varsigma_2 = 0;\ \xi_2 = 0 \tag{A3}$$

Ordinary least square (OLS) regression is used to solve equation (A2), or equation (A3), at a chosen $T_{B,1}$ using the 't-sig' method (Perron, 1997, p.359). In this method, regression is started at a user specified maximum value for k (denoted by $k_{\max}$) and is repeated at values of k in the range of $k_{\max}$ to 1 in an descending order until η_k becomes significant at 10% level for the first time. Estimated break year, denoted by $\hat{T}_{B,1}$, is the year in which absolute value of the t-statistic of $\hat{\theta}_1$ becomes maximum. Having chosen the appropriate break year, unit root null will be tested using the following nonlinear equivalent of equations (A2) and (A3):

$M1_{1B,NL}$: Equation (A1) with $\theta_1 = \phi + \varphi;\ \varsigma_1 = \phi - \alpha\varphi;\ \xi_1 = 0;\ \theta_2 = 0;\ \varsigma_2 = 0;\ \xi_2 = 0$

$M2_{1B,NL}$: Equation (A1) with $\theta_1 = \phi + \varphi;\ \varsigma_1 = \phi - \alpha\varphi;\ \xi_1 = -\alpha\phi;\ \theta_2 = 0;\ \varsigma_2 = 0;\ \xi_2 = 0$

Nonlinear test regressions were carried out at $\hat{T}_{B,1}$ with appropriate lag k selected by the 't-sig' method using the nonlinear least square regression method. Resulting t-statistic corresponding to $\hat{\alpha}$, denoted by $t_{\hat{\alpha},NL}(\hat{T}_{B,1})$, is tested for unit root null against appropriate critical values Popp (2008). This two-step procedure is recommended since it is claimed that the linear test regression identifies the break date more accurately than the corresponding nonlinear test, and that the nonlinear test offers a powerful unit root test even in finite sample (Popp, 2008, p.7-8).

Next, the trending time series is tested for two structural breaks using the following linear test equations (Narayan & Popp, 2010):

$M1_{2B,L}$: Test equation for two breaks in the level of a trending series:

$$\text{Equation (A1) with } \xi_1 = 0;\ \xi_2 = 0 \tag{A4}$$

$M2_{2B,L}$: Test equation for two breaks in the level and slope of a trending series:

Equation (A1) with all non-zero coefficients

In the sequential procedure suggested by (Narayan and Popp, 2010), starting with the already chosen first break date $\hat{T}_{B,1}$, a second break date $\hat{T}_{B,2}$ (> $\hat{T}_{B,1}$ +2) is selected by solving equation (A4), or equation (A1), and by locating the maximum absolute t-statistic of $\hat{\theta}_2$ for equation (A4), or equation (A1). The t-statistic corresponding to $\hat{\alpha}$, denoted by $t_{\hat{\alpha},L}(\hat{T}_{B,2})$, is tested for unit root null against appropriate critical values (Narayan & Popp, 2010).