Fossil fuel based CO2 emissions, economic growth, and world crude oil price nexus in the United States

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Abstract

With the prime objective of learning from the fossil fuel based CO_2 emissions-economic growth-world crude price nexus of a leading economy, the underpinning nature of the relationship among them is investigated for the United States (US). Autoregressive distributed lag bounds testing approach to cointegration provides empirical evidence for the existence of a long-run equilibrium relationship with 1% growth in GDP being tied up with 3.2% growth in CO_2 emissions in the US. Increase in crude price and technological progress, proxied by time trend, are associated with decline in CO_2 emissions in the long-run, though by comparatively small magnitudes. Short-run dynamics restore 25% of any disequilibrium in a year. Owing to the structural breaks identified in the individual series by the unit root tests, the stability of the model coefficients over the sample period is tested using the cumulative sum of recursive residuals test and ascertained. Error-correction based Granger causality tests provide evidence for fluctuating world crude real price Granger causing fluctuations in CO_2 emission, and fluctuating CO_2 emission Granger causing the rise and fall of real GDP. Deviations from long-run equilibrium are seen to Granger cause changes in both the CO_2 emissions and the real GDP in the US.

Keywords: Carbon dioxide emissions; cointegration; crude oil price; forecast; Granger causality; gross domestic product; GDP; United States.

1. Introduction

A century after the pioneering work of Svante August Arrhenius [1], who studied the influence of atmospheric carbon dioxide (CO_2) concentration upon global surface temperature, the Intergovernmental Panel on Climate Change (IPCC) concluded that fossil fuel use was responsible for significant increase in atmospheric concentrations of greenhouse gases (GHG), inclusive of CO_2 [2]. A recent report of the IPPC [3] states that average global surface temperature is likely to rise 1.1 to 6.4°C 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 (abbreviated US henceforth) 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, and it still has not. Several countries that have ratified the Kyoto Protocol have amplified emission reduction targets to attain compliance with the Kyoto Protocol commitments before 2012. It must be noted, however, that the Kyoto Protocol is considered inadequate in slowing down the GHG-induced global warming and the resulting climate change by a number of researchers (see, for example [4,5]).

In high income economies, such as the US, service sector dominates over manufacturing sector [6], and changes in electricity-mix take place [7,8]. These factors together with technological progress have led to the popular belief that environmental pollution, inclusive of GHG emissions, in a country might decrease with income once the country surpasses a threshold income [9,10]. This is known as the Environmental Kuznets Curve (EKC) hypothesis, and was introduced to the scientific pollution literature by the incipient research studies of Grossman and Krueger [11], Shafik and Bandyopadhyay [12], Panayotou [13], Selden and Song [14], and Holtz-Eakin and Selden [15], among others.

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 (US Congress [16]; Pravda [17]; Commonwealth of Australia [18]).

A recent inventory of GHG emissions and sinks in the US from 1990 to 2008 [19] 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, by the US Environmental Protection Agency [19], to the generally growing domestic economy, energy price fluctuations, and technological changes.

This paper investigates the existence or the absence of a long-run equilibrium 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 evidence for the existence of a long-run equilibrium relationship among the variables considered.

Cointegration testing methodology used in this study is the autoregressive distributed lag (ARDL) bounds testing approach to cointegration (Pesaran and Shin [20]; Pesaran et al. [21]. Even though ARDL approach requires no pre-testing to identify the order of integration of the time series considered, asymptotic and finite-sample critical value bounds provided by Pesaran et al. [21] and Narayan [22], respectively, are valid for series with order of integration not exceeding unity. It is therefore, the time series data used in this study are tested for unit roots using a recently developed nonlinear unit root test in the presence of a single structural break (Popp [23]), and a linear test in the presence of two structural breaks (Narayan and Popp, [24]).

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 (Oxley and Greasley [25]; Ghosh [26]; Narayan and Singh [27]; Acaravci and Ozturk [28]). 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 as feared by the Byrd-Hagel Resolution [16] which was not in favour of the US being party to the Kyoto Protocol. 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.

Prime objective of the above analyses is to learn from the economic development path followed by a leading high income economy of the world, since low and medium income economies tend to follow the established economic development path of high income economies such as the US. If the economic growth in the US is CO_2 emission dependent then imitating such development path shall not be beneficial for developing countries in a world that is taking serious steps to curb CO_2 and other GHG emissions.

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, brief account of the econometric methodologies used is given in Section 4, and empirical results and discussion in Section 5. Fossil fuel based CO_2 emissions projections till 2035 are presented in Section 6 along with the uncertainty analysis, and Section 7 concludes.

2. CO_2 emission-economic growth 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 so that economic growth, by itself, may solve environmental problems [9,10]. While Shafik and Bandyopadhyay [12] and Shafik [29] found CO_2 emissions per capita to increase with rising per capita income within the sample periods studied, Dijkgraaf and Vollebergh [30] and Schmalensee et al. [31] 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 [32] concluded that emission-income relationship monotonically rises for global pollutants, such as CO_2. Perman and Stern [33] 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 [34] who found cointegration between Austrian yearly emissions and income time series during 1960-1999. Aldy [7] 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 [35] carried out a panel data-based cointegration analysis for 88 countries with annual data in the range of 1960-1990. Their results showed null 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. [36] 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 [37] 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 [38], five OPEC countries [39], Turkey [40], India [41], and for 19 European countries [28], 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 [42] first showed, using phase diagrams, that per capita CO_2 emissions 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 [43] 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 [34] 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 [44], 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 [45] 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. When combined with the technological trend effects, he observed, CO_2 emissions would decline only if real GDP per capita growth was maintained below 1.8%.

Shanthini and Perera [46] 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 [47] who used the ARDL bounds testing approach [20,21] for the first time to study the emissions-income-crude price nexus of a nation. A conditional equilibrium correction model (ECM) developed by them forecasted fossil fuel-based CO_2 emissions in Australia to grow by 36 to 40% in 2020 over the 2000 level even for per capita GDP growth rates as low as 0.7 to 1.4%. Their study also 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, the results of which show world crude oil real price have considerable impact on the CO_2 emission-economic growth nexus of the US.

3. Data used and model rationale

Fig. 1 shows the variations in annual CO_2 emissions stemming from fossil-fuel burning, cement manufacture and gas flaring in the US against her annual real GDP during 1950-2007. Historical CO_2 emissions data (in $MtCO_2$[1]) are obtained from the Carbon Dioxide Information Analysis Center of the US Department of Energy [48] and real GDP data (in

[1] $MtCO_2$ stands for megatonne (= 10^9 kg) of CO_2 equivalent

billions of constant 2005$) are obtained from Bureau of Economic Analysis [49]. 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 (see Fig. 1). Choice of the end year as 2007 was dictated by CO_2 emissions data availability in the data source [48] used.

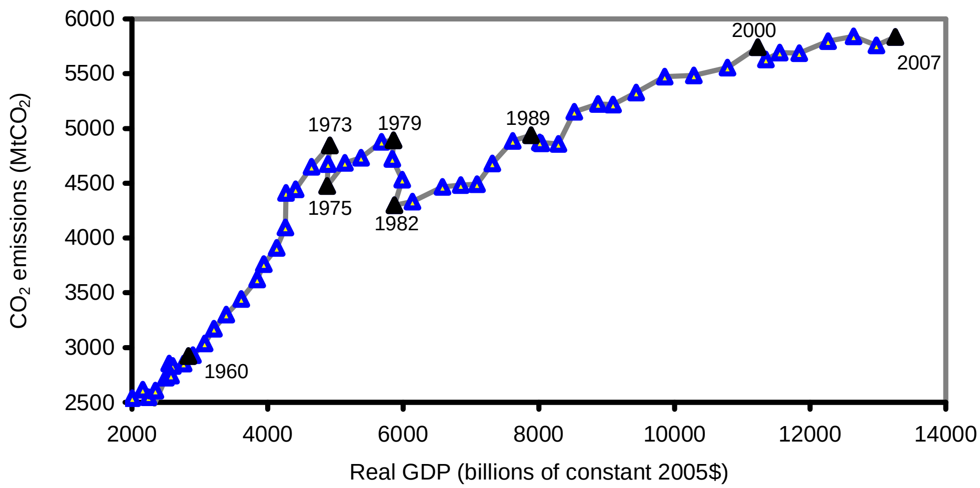

Fig. 1. Annual fossil fuel-based CO_2 emissions in the United States against her annual real gross domestic product during 1950 to 2007.

As seen in Fig. 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.

Fig. 2 shows the annual variations in average world crude oil real price (British Petroleum [50]) 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.

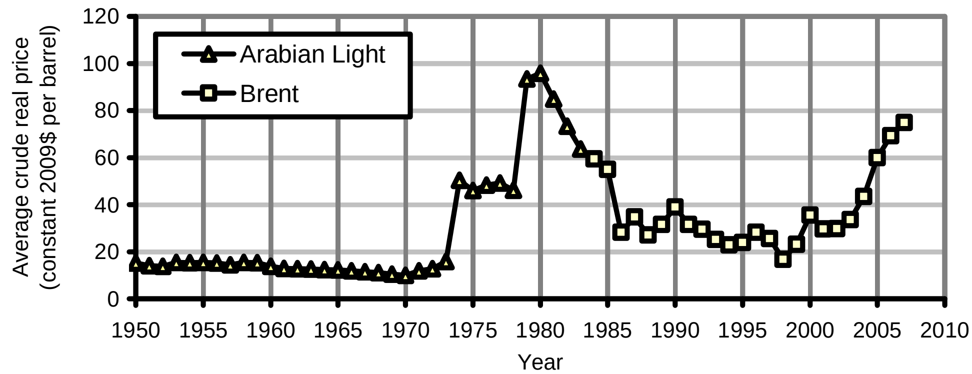

Fig. 2. Average world crude oil real price during 1950 to 2007.

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 (Fig. 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 (Fig. 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 [45] 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, real GDP 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 (Fig. 1 and Fig. 2), and therefore augmented Dickey-Fuller and other conventional tests may not correctly identify the order of integration [51]. 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 [23] and Narayan and Popp [24]. 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 and Popp [24,52]). Moreover, the unit root test of Popp [23] 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 elaborated below.

The most general test equation underlying the abovementioned tests for a trending series is as follows:

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

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 [23]:

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

Equation (1) with $\xi_1 = 0;\ \theta_2 = 0;\ \varsigma_2 = 0;\ \xi_2 = 0$ (2)

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

Equation (1) with $\theta_2 = 0;\ \varsigma_2 = 0;\ \xi_2 = 0$ (3)

Ordinary least square (OLS) regression is used to solve Eq.(2), or Eq.(3), at a chosen $T_{B,1}$ using the '*t*-sig' method ([53], 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 Eq.(2) and Eq.(3):

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

$M2_{1B,NL}$: Eq.(1) 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 [23]. 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 ([23], p. 7-8).

Next, the trending time series is tested for two structural breaks using the following linear test equations [24]:

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

Eq.(1) with $\xi_1 = 0;\ \xi_2 = 0$ (4)

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

Eq.(1) with all non-zero coefficients

In the sequential procedure suggested by Narayan and Popp [24], 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 Eq.(4), or Eq.(1), and by locating the maximum absolute t-statistic of $\hat{\theta}_2$ for Eq.(4), or Eq.(1). 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 [24].

Order of integration of the time series are also tested using conventional unit root testing methodologies, namely augmented Dickey-Fuller test, GLS-detrended Dickey-Fuller test, Phillips-Perron test, and Kwiatkowski, Phillips, Schmidt and Shin test, abbreviated ADF, DF-GLS, PP and KPSS, respectively. The first three tests have the null hypotheses that the time series tested contains a unit root, i.e. the series is non-stationary, and the KPSS test has the null of the tested series being stationary. These tests, carried out using the built-in test routines available with the statistical package EViews 6 from Quantitative Micro Software LLC, are not elaborated here owing to their popular use in cointegration and Granger causality literature.

4.2. ARDL cointegration analysis

ARDL bound testing approach to cointegration [20,21] is used in this study since it is based on a single equation approach which is shown to be theoretically superior and efficient [54,55], among many other reasons (see, for example, [28]). First step in the ARDL approach is to estimate the following unrestricted ECM.

$$\Delta C(t) = \beta_0 + \beta_1 C(t-1) + \beta_2 G(t-1) + \beta_3 O(t-1) + \beta_4 (t-1950) + b_0 \Delta G(t) + d_0 \Delta O(t)$$
$$+ \sum_{i=1}^{m} a_i \Delta C(t\text{-}i) + \sum_{i=1}^{n} b_i \Delta G(t\text{-}i) + \sum_{i=1}^{p} d_i \Delta O(t\text{-}i) + \varepsilon(t) \qquad (5)$$

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 of Narayan [22]. 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:

$$ARDL(m,n,p):\ C(t) = \mu_0 + \mu_t (t-1950) + \sum_{i=1}^{m} \gamma_i C(t\text{-}i) + \sum_{j=0}^{n} \tau_j G(t\text{-}j) + \sum_{k=0}^{p} \rho_k O(t\text{-}k) + ECT(t) \quad (6)$$

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 suggested in Pesaran and Shin [20]. 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 [21].

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 [25,26,27,28]:

$$\begin{aligned}\begin{bmatrix}\Delta C(t)\\ \Delta G(t)\\ \Delta O(t)\end{bmatrix} &= \begin{bmatrix}\kappa_1\\ \kappa_2\\ \kappa_3\end{bmatrix} + \begin{bmatrix}\lambda_{11,1} & \lambda_{12,1} & \lambda_{13,1}\\ \lambda_{21,1} & \lambda_{22,1} & \lambda_{23,1}\\ \lambda_{31,1} & \lambda_{32,1} & \lambda_{33,1}\end{bmatrix}\begin{bmatrix}\Delta C(t-1)\\ \Delta G(t-1)\\ \Delta O(t-1)\end{bmatrix}\\ &+ \mathrm{K} + \begin{bmatrix}\lambda_{11,p} & \lambda_{12,p} & \lambda_{13,p}\\ \lambda_{21,p} & \lambda_{22,p} & \lambda_{23,p}\\ \lambda_{31,p} & \lambda_{32,p} & \lambda_{33,p}\end{bmatrix}\begin{bmatrix}\Delta C(t-p)\\ \Delta G(t-p)\\ \Delta O(t-p)\end{bmatrix} + \begin{bmatrix}\pi_1\\ \pi_2\\ \pi_3\end{bmatrix} ECT(t-1) + \begin{bmatrix}v_1\\ v_2\\ v_3\end{bmatrix}\end{aligned} \tag{7}$$

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: $\lambda_{12,1} = \lambda_{12,2} = \mathrm{K} = \lambda_{12,p} = 0$ 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. Empirical results and discussion

5.1. Order of integration of the time series

ADF, DF-GLS, PP and KPSS test statistics, obtained using EViews6, are tabulated in Table 1. First three test statistics do not reject the unit root null at level and reject the unit root null at first difference for all three variables. KPSS test statistics rejected the null of stationarity at level for all series but *O*. Therefore, I concluded that *C* and *G* are $I(1)$ series. No conclusion could be reached in case of *O*. The contradictory results obtained with *O* called for the use of unit root testing methodologies incorporating structural breaks. Results obtained with such testing methodologies [23,24], outlined in Section 4.1, are tabulated in Tables 2 and 3.

Since the primary interest is the unit root properties of the series tested, test statistics $t_{\hat{\alpha},NL}(\hat{T}_{B,1})$ and $t_{\hat{\alpha},L}(\hat{T}_{B,2})$, tabulated in Tables 2 and 3, 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, inclusive of the crude oil real price, are $I(1)$ series at 5% level of significance. This result contrasts that of Jalali-Naini and Asali [56] who reported crude real price cycles were both mean reverting and not shock-persistent.

It is noteworthy to mention that all 12 models tested have highly significant coefficients of the break dummies, $\hat{\theta}_1$ and $\hat{\theta}_2$. For crude real price, both M1 and M2 models identify the first and the second break years 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 2). For real GDP, both models identify the first break year 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*.

Table 1.
Conventional unit root test statistics

Test	C	ΔC	G	ΔG	O	ΔO
ADF	-1.34^{ns}	-6.32***	-2.22^{ns}	-5.49***	-1.71^{ns}	-7.05**
DF-GLS	-1.32^{ns}	-6.42***	-1.97^{ns}	-6.20***	-1.75^{ns}	-7.13***
PP	-1.25^{ns}	-6.32***	-2.52^{ns}	-7.93***	-1.99^{ns}	-7.06***
KPSS	0.15**	0.09^{ns}	0.16**	0.09^{ns}	0.09^{ns}	0.09^{ns}
Conclusion	C is an $I(1)$ series		G is an $I(1)$ series		KPSS test results contradict the other test results	

Note: Symbol Δ denotes first difference. Symbols *** and ** indicate significance at the 1% and 5% levels, respectively. Symbol ^{ns} indicates non-significance even at the 10% level. Test statistics of DF-GLS tests are based on the automatically selected lag lengths using Hannan-Quinn Criterion with the user specified maximum lag of 10, and those of PP and KPSS tests are based on the automatically selected Newey-West bandwidth using Parzen kernel. The series tested is assumed to be trending with an intercept for all tests.

Table 2.
Test statistics of unit root tests with structural break(s) in the level (model M1).

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 ** are 1% and 5% significance levels, respectively, and ^{ns} indicates non-significance even at 10% level. All other notations used are defined in section 4.1. Results of the non-linear model 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 [24] and table 3 of Narayan and Popp [25], respectively.

Table 3.
Test statistics of unit root tests with structural break(s) in the level and slope (model M2).

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.

5.2. Cointegration

As the next step, cointegration among *C*, *G* and *O* is tested using the ARDL bound testing procedure briefed in Section 4.2. Both AIC and SC statistics select the optimum lag lengths in Eq.(5) 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 [57]. 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 ([22], 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 Eq.(5), 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 ([22], 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 [20]:

$$ARDL(1,4,1):\ C(t) = -\underset{[-7.62]}{16.2359} - \underset{[-9.68]}{0.0899}(t-1950) + \underset{[11.28]}{3.2028}G(t) - \underset{[-2.82]}{0.0776}O(t) + ECT(t) \quad (8)$$

where t-statistics, given within the brackets, are computed using the Delta method [20], 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 Eq.(8).

Long-run equilibrium estimates in Eq.(8) 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 grow 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 short-run dynamic equation:

$$\begin{aligned}\Delta C(t) = &-\underset{[-2.71]}{0.0224} - \underset{[-6.23]}{0.2529}\,ECT(t-1) + \underset{[8.65]}{0.9945}\,\Delta G(t) - \underset{[-2.30]}{0.3196}\,\Delta G(t-1) \\ &- \underset{[-3.71]}{0.4796}\,\Delta G(t-2) - \underset{[-2.12]}{0.2861}\,\Delta G(t-3)\end{aligned} \quad (9)$$

where *ECT(t-1)* is given by Eq.(8), and the statistical significance of the estimated parameters are testified by the corresponding *t*-statistics given within the brackets below the parameters concerned.

Eq.(9) 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 Fig. 3, confine themselves within the critical bounds of 5% significance. This implies the estimated coefficients of Eq.(9) are nearly constants from one sample period to the other, despite crude real price series experiencing two structural breaks within the sample period.

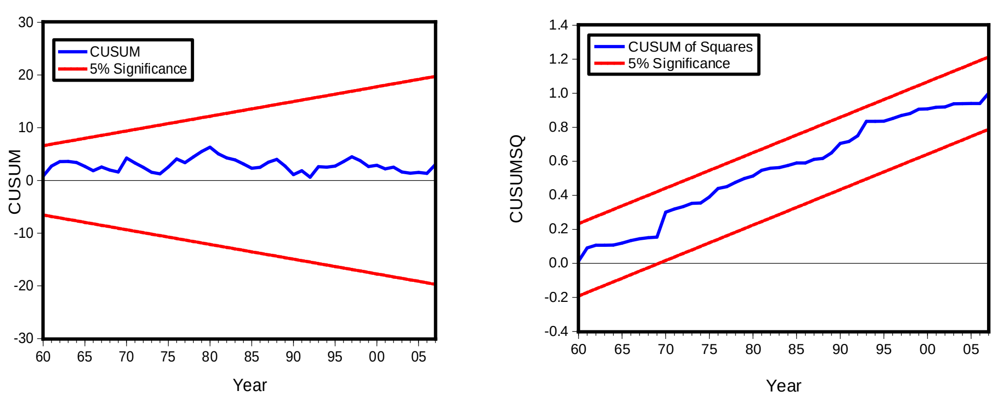

Fig. 3. Cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares of recursive residuals (CUSUMSQ) of the ECM of Eq.(9).

In interpreting Eq.(9), 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 [60]. 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 Eq.(8), the long-run and the short-run Granger causalities are analyzed using the procedure briefed in Section 4.4. SC selected an optimum lag length of one in Eq.(7) 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 4.

Table 4 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.

Table 4.
Results of error-correction based Granger causality tests.

Dependent variable	*F*-statistics of the explanatory variables			coefficients of $ECT(t\text{-}1)$
	$\Delta C(t)$	$\Delta G(t)$	$\Delta O(t)$	
$\Delta C(t)$	-	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 ** are 1% and 5% significance levels, respectively. P-values are provided within the parenthesis.

Empirical evidence, therefore, suggests, as could be visualized in Fig. 4, fluctuating world crude oil real price Granger causes fluctuations in CO_2 emission, which in turn Granger causes the rise and fall of real GDP. Deviations from long-run equilibrium Granger cause changes in both CO_2 emission and real GDP. Long-run causality results therefore corroborate with the ARDL bounds test results presented in Section 5.1 which provide empirical evidence for cointegration with either C or G as dependent variable.

In contrast to the results presented above, Granger causality results of Soytas et al. [36] provide no evidence for long-run causality (in any direction) between CO_2 emissions and real GDP in the US. It must be noted that Soytas et al. approach did not include crude real price as one of the explanatory variables.

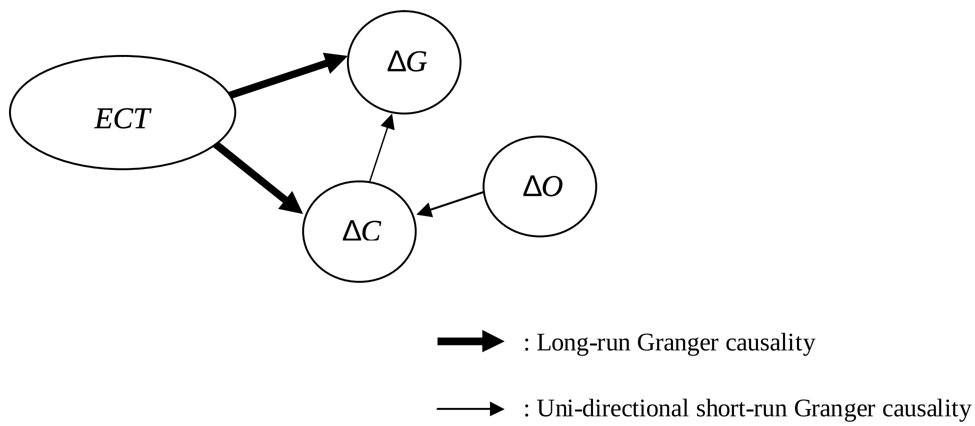

Fig. 4 Granger causality dynamics. ΔC, ΔG and ΔO represent relative growths in CO_2 emissions, real GDP and world crude oil real price, and *ECT* represent deviation from the long-run equilibrium among the three variables at level.

It must be noted that the magnitude of the coefficient of the lagged *ECT* term in the CO_2 emission equation is -0.113 (Table 4) whereas it is -0.253 in the short-run dynamic equation, Eq.(9). Reason for this is the absence of the current real GDP in the Granger causality equation, Eq.(7), using which one assesses the impact of the past values of real GDP upon the current value of CO_2 emissions. However, one year is too long a period to assume that real GDP of the current year may not have caused changes in current year's CO_2 emissions. While we bear with this limitation of the Granger causality analysis, ARDL bounds testing approach [20,21] overcomes this limitation by the use of current value of real GDP in estimating the short-run dynamic equation.

5.6. Sufficiency of the model developed

Results reported in the preceding sections are based on the assumption CO_2 emissions in the US could sufficiently be explained by real GDP, crude real price, and time trend. As already pointed out elsewhere in this paper, time trend is used as a proxy for technological progress and other emissions reductions policies and strategies which have evolved during the past half century. Since non-fossil fuel use in the US has increased by 5 folds between 1950 and 2007 [49] and the energy intensity of economic activity has halved during this period [49], it is likely that they have been contributing towards the reduction of CO_2 emissions. I therefore extended the analysis to search for cointegration among CO_2 emissions, real GDP, crude real price, non-fossil fuel based energy consumption (denoted by EC_{NF}), and energy consumption per real GDP (denoted by *EC/GDP*). Results obtained are tabulated in Table 5 and Table 6.

Table 5.
Cointegration test results with *C* as dependent variable for a sample of 1955-2007.

Variables included in the cointegration test	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
C	P	P	P	P	P	P
G	P	P	P	P	P	P
O	P		P		P	
$\ln(EC_{NF})$	P	P			P	P
ln(*EC/GDP*)	P	P	P	P		
Testing for cointegration with trend						
F-statistic	2.426	3.168	2.193	2.486	7.749	6.544
Lower bound critical value	3.383	3.730	3.730	4.225	3.730	4.225
Upper bound critical value	4.432	4.666	4.666	5.030	4.666	5.030
Testing for cointegration without trend						
F-statistic	2.273	3.189	1.933	2.538	3.973	2.604
Lower bound critical value	3.136	3.500	3.500	4.070	3.500	4.070
Upper bound critical value	4.416	4.700	4.700	5.190	4.700	5.190

Notes: EC_{NF} and *EC/G* are the natural logarithms of annual non-fossil fuel based energy consumption in the US and the natural logarithms of annual energy consumption per real GDP. Critical values provided are at the 5% level of significance for a sample size of 50 [22].

Table 6.
CO_2 emissions long-run elasticities.

Model	*Intercept*	*Trend*	*G*	*O*	$\ln(EC_{NF})$
5	-7.251	-0.0504 (-4.12)	1.981 (5.25)	-0.0857 (-3.06)	0.0356 (0.37)
6	-13.563	-0.0776 (-6.05)	2.924 (7.45)		-0.1099 (-1.33)

Note: Listed within the parenthesis are *t*-statistics.

Table 5 lists the *F*-statistics computed with different combinations of the variables considered with and without the trend term, and the corresponding critical bounds. A closer look at the results reveals that the *F*-statistics are above the upper bound critical values for Model 5 and Model 6 with trend included. Therefore, I concluded that no cointegration can be rejected among CO_2 emissions, real GDP, EC_{NF}, and trend with and without crude real price. In all other cases tabulated in Table 5, null of no cointegration cannot be rejected.

Table 6 shows that long-run elasticity estimates of Model 5 and Model 6. They are statistically significant in all cases but in the case of EC_{NF}. In the absence of crude price, however, long-run elasticity of EC_{NF} at least takes the anticipated negative sign (Model 6) implying growth in EC_{NF} is associated with reduction in emissions. Long-run elasticity of EC_{NF} becomes positive once crude price is added (Model 5) implying the inappropriateness of EC_{NF} in a long-run relationship consisting of CO_2 emissions, real GDP, crude real price, and trend. in Model 5, long-run elasticity of crude price takes the correct sign, and it is statistically significant.

It is therefore evident that either increasing non-fossil fuel use or improving energy intensity of economic activity does not make a significant contribution towards changes in CO_2 emissions in the US. It is noteworthy that Sadorsky [58] also found no cointegration among non-conventional renewable energy consumption, real GDP, CO_2 emissions and real oil price in the US. Moreover, his results showed that increasing oil price decreases non-conventional renewable energy consumption in the US. Hamilton and Turton [59] has pointed out that the impressive progress made by the US in increasing its energy intensity of economic activity did not result in significant reduction in the emissions owing to her high population growth and large increase in the electricity consumption.

6. Forecasting results

6.1. Forecast equation

Following Amarawickrama and Hunt [61], forecast equation is derived by substituting the long-run equilibrium relationship (Eq.8) into the short-run dynamic relationship (Eq.9) and then by simplifying it as follows:

$$\begin{aligned} C(t) = {} & 0.7471C(t-1) + 0.9945G(t) - 0.5041G(t-1) - 0.1600G(t-2) + 0.1935G(t-3) \\ & + 0.2861G(t-4) - 0.0196O(t-1) - 0.0227(t-1951) - 4.1285 \end{aligned} \tag{10}$$

Fig. 5 shows CO_2 emissions obtained by dynamically simulating the above compound model, along with the actual CO_2 emissions values used for developing the model. 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 Fig. 5, compound model is able to closely predict the in-sample actual emissions, which is expected of the model considering the stability of the estimated coefficients of the ECM, reported in Section 5.4.

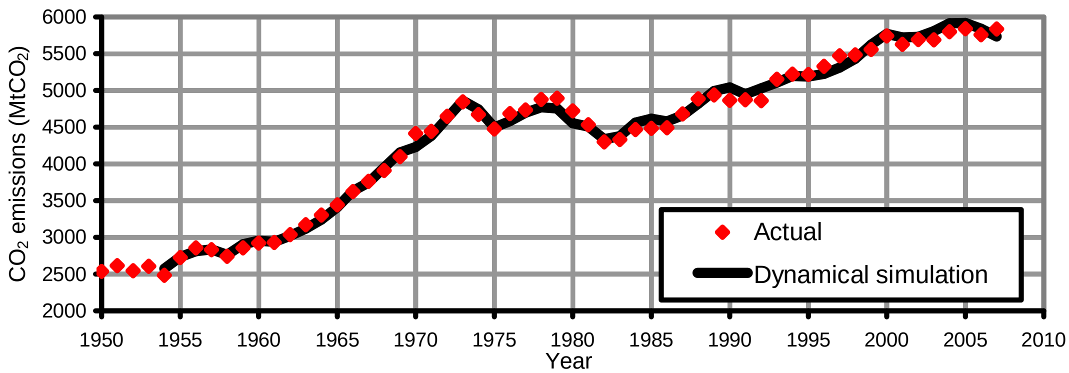

Fig. 5. Dynamically simulated CO_2 emissions using Eq.(10) compared with the actual values.

6.2. Forecast assumptions

The above compound model is used in this study to forecast fossil fuel based CO_2 emissions in the US beyond 2007. Any such future projections are known to suffer from uncertainties and therefore it is customary to develop several scenarios for the explanatory variables covering their potential ranges of uncertainties [61,62]. For 2008 and 2009, actual values of real GDP and crude real price available in the respective data sources are used. Beyond 2009, assumptions are required for real GDP growth and crude real price growth. In line with the approaches taken in past studies on forecasting with cointegration models [61,62], annual growth rates projections of the explanatory variables are obtained from existing official sources. One such source is the Annual Energy Outlook 2010 (abbreviated AEO2010) published by the US Energy Information Administration [63], which presents three economic growth scenarios in the US till 2035, and three world crude real price growth scenarios till 2035.

The economic growth scenarios of AEO2010 are based on various assumptions about labour force growth and productivity [64]. In all three scenarios, real GDP is assumed to decline by 0.9% from 2009 to 2010 reflecting the current economic recession. In the reference-economic-growth scenario, real GDP is assumed to grow by 3.0% from 2010 to 2020 and by 2.5% from 2020 to 2035. In the high-economic-growth scenario, these growth rates are 3.8% and 3.0%, respectively. In the low-economic-growth scenario, these growth rates are 2.3% and 1.8%, respectively. I used the above three scenarios for real GDP projections beyond 2009 till 2035, referring to them as 'AEO2010-reference', 'AEO2010-high' and 'AEO2010-low', respectively.

Forecast period is chosen to match that of AEO2010, and hence the upper limit is set at 2035. Moreover, since sizable reductions in fossil fuel based CO_2 emissions have taken central stage in today's world and policies have been drawn up as well as being implemented to that effect globally, forecasts made for business as usual scenarios in studies such as this one would, and should, be far above the actual emissions in decades to come, and thereby the choice of a short forecast horizon is justified.

In search of alternatives to the aforementioned real GDP growth rate scenarios, upon the recommendation of an anonymous reviewer, real GDP growth uncertainty is estimated using the following autoregressive integrated moving average (ARIMA) process developed with annual real GDP data in the range of 1929 to 2010 [65] using EViews 6:

$$\Delta G(t) = \underset{[15.8]}{0.0300} + u(t)$$

$$\begin{aligned}\left(1+\underset{[-1.85]}{0.1314}L^{4}\right)\left(1+\underset{[-8.9]}{0.5786}L^{4}\right)\left(1-\underset{[5.6]}{0.4382}L^{12}\right)u(t) \\ = \left(1+\underset{[3.5]}{0.4913}L^{4}-\underset{[-1.82]}{0.2291}L^{8}\right)\left(1-\underset{[-33.1]}{0.9105}L^{12}\right)\varepsilon(t)\end{aligned} \tag{11}$$

where L is the lag operator, $u(t)$ is the disturbance term, $\varepsilon(t)$ is the innovation in the disturbance, and t-statistics are provided within the brackets below the estimated coefficients.

Eq.(11) is estimated to have an adjusted R^2 of 61%, a Durbin Watson statistic of 1.81, Estimated chi-squared statistics of Breusch-Godfrey serial correlation LM test, Ljung-Box Q-statistic, Jarque-Bera normality test, and ARCH heteroskedasticity test are $\chi^2_{SC}(4) =$ 1.85 [0.76], $\chi^2_{LB}(7) =$ 2.70 [0.10], $\chi^2_{N}(2) =$ 1.29 [0.52], and $\chi^2_{H}(1) =$ 0.21 [0.64], respectively. P-values of the given F-statistics and 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.

Dynamic forecast of $G(t)$ is generated by the above ARIMA process from 2011 to 2035 and the forecast standard errors are estimated. Dynamic forecast of $G(t)$ is taken to describe the fourth economic growth scenario, termed as 'ARIMA-reference'. Forecast boundaries enclosing the projected real GDP uncertainty are described by adding and subtracting twice the estimated forecast standard errors to the dynamically forecasted *G(t)*. These boundaries define 'ARIMA-high' and 'ARIMA-low' economic growth scenarios, respectively.

Fig. 6 shows that real GDP projections along ARIMA scenarios are above their respective AEO2010 scenarios. The reason for this difference is real GDP is assumed to decline by 0.9% from 2009 to 2010 in the AEO2010 scenarios, whereas ARIMA scenarios use the fact real GDP has grown by 2.8% during this period [65]. Real GDP at 2035 becomes 1.7 times its 2005 value along AEO2010-low scenario which defines the lower boundary of the uncertainty regime of real GDP projections. Real GDP at 2035 becomes 2.7 times its 2005 value along ARIMA-high scenario which defines the upper boundary.

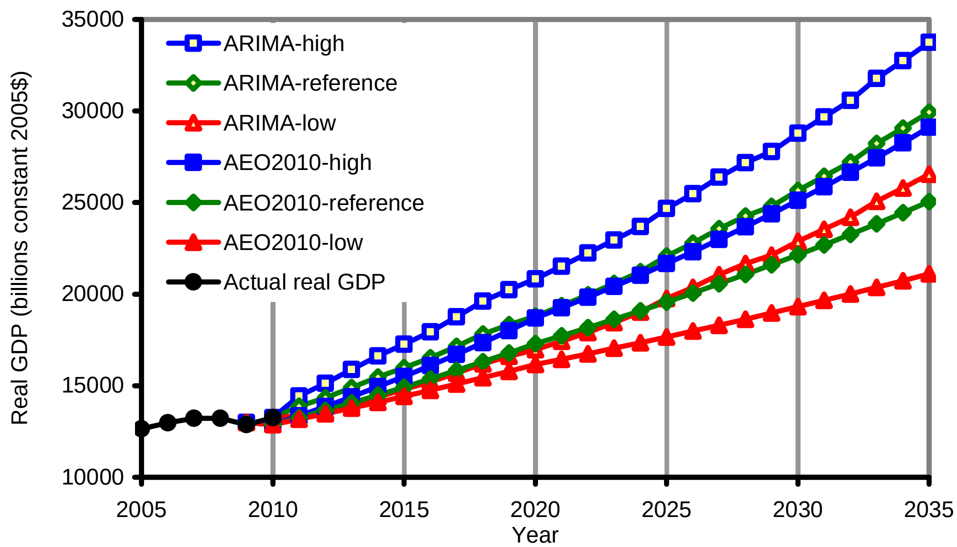

Fig. 6. Real GDP projections beyond 2009 for hypothetical economic growth scenarios considered.

In case of the world crude real price beyond 2009, this study uses the same three scenarios that are used in AEO2010 [66]. In all three scenarios, crude price is 70 constant 2008$ in 2010. In 2020, crude prices are projected at 52, 108 and 185 constant 2008$ in the low-crude-price, reference-crude-price and high-crude-price scenarios, respectively. In 2035, they are 51, 133 and 209 constant 2008$, respectively. Owing to the structural breaks identified in the crude real price variable, and because of the comparatively low impact of crude real price on CO_2 emissions, as in Eq.(10), no attempt is made in this study to develop additional crude real price growth scenarios.

6.3. Forecasts

CO_2 emissions forecasts made from 2008 till 2035 for the six economic growth scenarios considered, holding crude real price growth rate at its reference value, are shown in Fig. 7. It is noteworthy that fossil fuel based CO_2 emission projection falls below its 1990 level and remains there till about 2020 in all cases except the ARIMA-high economic growth case. Percentage increases in CO_2 emissions at 2035 from the 1990 emission level for all 18 scenarios considered in this study are tabulated in Table 7. Results shown in Fig. 7 and Table 7 reveal that the US could realize sizable reductions in its fossil-fuel based CO_2 emissions from its 1990 emissions levels in AEO2010-low, ARIMA-low, and AEO2010-reference economic growth scenarios. Along AEO2010-high economic growth scenario, CO_2 emission in the US in 2035 becomes 2%, 6%, or 13% above its 1990 level, for high-, reference-, or low-, crude-price scenarios, respectively. It must be noted that the long-term real GDP growth rate is set at 3% for the AEO2010-high economic growth scenario [64].

In case of real GDP growth rate in the US exceeding 3%, fossil fuel based CO_2 emissions levels in the US reach levels that would be most unwelcome from the global warming point of view (Fig. 7 and Table 7). It must be borne in mind that the forecasts made in this study for quarter of a century ahead are meaningful only for a business as usual scenarios in which CO_2 emissions curbing technologies, life styles and policies are assumed to undergo no radical changes in the future.

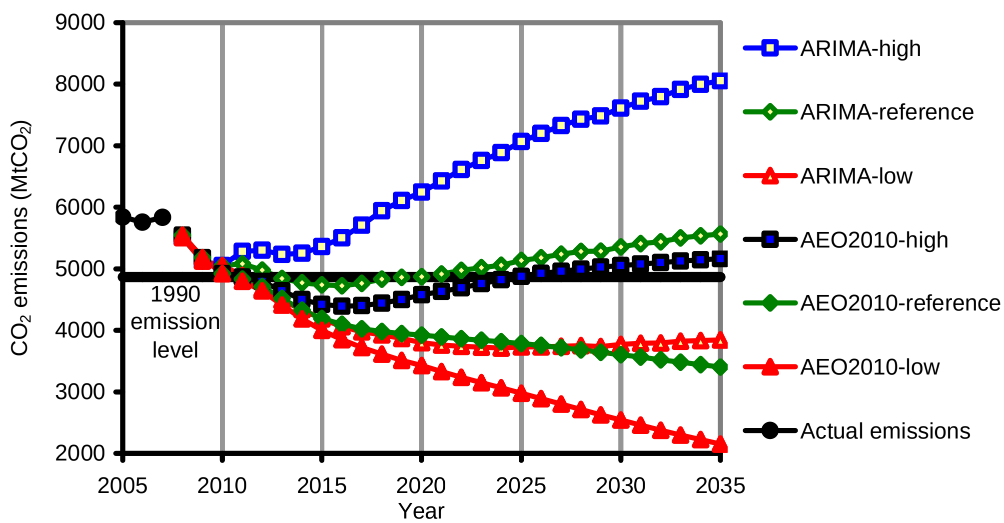

Fig. 7. CO_2 emissions forecasts using Eq.(10) for hypothetical economic growth scenarios beyond 2009 while holding crude real price growth rate at AEO2010 reference-crude-price scenario.

Table 7.
Percentage increases in CO_2 emissions at 2035 from its 1990 level for 18 different hypothetical scenarios considered in this study.

Real GDP growth rate scenarios since 2010	AEO2010 crude real price growth rate scenarios since 2010		
	High-crude -price	Reference-crude -price	Low-crude -price
ARIMA-high	59%	65%	77%
ARIMA-reference	10%	14%	22%
ARIMA-low	-24%	-21%	-15%
AEO2010-high	2%	6%	13%
AEO2010-reference	-33%	-30%	-25%
AEO2010-low	-57%	-55%	-53%

7. Conclusion

Long-run equilibrium relationship is established in this study among fossil fuel based CO_2 emissions in the US, her real GDP, and world crude real price. The estimated long-run income elasticity of CO_2 emission in the US is 3.2, and crude price elasticity is -0.08. Progressive technological and policy-based CO_2 emissions reduction strategies, proxied by time trend, under constant crude real price scenario, cause CO_2 emissions to decline in the US only if real GDP grow at a rate less than 2.8%.

Error-correction based Granger causality analyses carried out in this study reveals fluctuating world crude real price Granger causes fluctuations in CO_2 emissions, which in turn Granger cause the rise and fall of real GDP. Deviations from long-run equilibrium Granger cause changes in both CO_2 emissions and the GDP so as to correct the deviations within a 4-year period.

This study therefore provides empirical evidence for the fossil-fuel based CO_2 emission-dependence of the economic growth in the US, which requires technological as well as policy-wise intervention to eliminate the emissions dependence of economic growth in a post-Kyoto global environment. Fast-growing low and the middle income economies tend to adopt CO_2 emissions intensive technological and policy solutions to attain high-income status trusting that CO_2 emission reduction is plausible once the economy is grown to satisfactory levels (the familiar EKC hypothesis). The results of this study clearly demonstrate that it is the rate of economic growth and not the level of economy that decides the CO_2 emission intensity of a high income economy such as the US. Thus, it is amply clear that investing on

CO_2 emissions intensive policies and technologies might bring a country to a vulnerable status where she needs to decide between CO_2 emissions reduction and economic growth, particularly in a world that is taking emissions reduction seriously.

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