Published in revised form in Int. J. Oil, Gas and Coal Technology 2010:3(2):182-200

Is there a cointegrating relationship between Australia's fossil-fuel based carbon dioxide emissions per capita and her GDP per capita?

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Abstract: Carbon dioxide (CO_2) emission per capita of Australia, a high-income economy with a fossil fuel-rich fuel-mix, is proven to have a strong cointegrating relationship with her gross domestic product (GDP) per capita. A conditional equilibrium correction model (ECM) has been developed to quantify the relationship between the two variables by employing the autoregressive distributed lag bound-testing approach to cointegration. The long-run income elasticity is estimated to be as high as 0.7, and 36% of any deviation from the long-run equilibrium is corrected within a year. In the short-run, 1% increase in GDP per capita growth in the previous year leads to 0.33% increase in the current growth in CO_2 emission per capita. The conditional ECM developed is robust against functional form misspecification and have stable regression coefficients over the sample period studied. Thus, it could be used to reliably predict the future CO_2 emissions in Australia.

Keywords: ARDL; Australia; carbon dioxide; cointegration; ECM; emission modelling; equilibrium correction; GDP per capita; long-run equilibrium; short-run dynamics.

1 Introduction

Incipient research studies on carbon dioxide (CO_2) emission modelling (Shafik, 1994; Shafik and Bandyopadhyay, 1992) found the CO_2 emission to monotonically increase with rising income. Schmalensee, Stoker, and Judson (1998), however, contradicted the above and showed that the relationship between per capita CO_2 emission and per capita income describes an 'inverse-U-shaped' (quadratic) relationship, known as the Environmental Kuznets Curve (EKC). They located falling per capita CO_2 emission with rising income at per capita income levels reached in high-income economies during the 1970s. The 'inverse-U-shaped' relationship was foreseen by de Bruyn, van den Bergh, and Opschoor (1998) as a temporary phenomenon that was on its way to grow into an 'N-shaped' (cubic) relationship. Econometric evidence was found for the existence of 'N-shaped' relationship between CO_2 and income for a single country (Friedl and Getzner, 2003) as well as for a group of countries (Galeotti and Lanza, 2005).

In explaining the 'N-shaped' relationship between emission and income, de Bruyn (2000) observed that pollution reduction initiatives taken by some economies may have ceased 'once the technological opportunities for further reductions have been exhausted or have become too expensive'. Carrying out a comprehensive survey of the empirical evidence and of

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possible causes of the EKC, Lieb (2003) concluded that 'for a given pollutant an EKC will only exist when policy measures are taken with respect to this pollutant'. Lieb also observed, however, that the emission-income relationship monotonically rises for global pollutants, such as CO_2.

The phase diagram analysis of Unruh and Moomaw (1998) showed that the reduction in the rate of increase in per capita CO_2 emissions in some of the high-income economies during the 1970s was caused by the 'oil shocks of the 1970s', during which the economically prosperous countries looked for alternatives to raise their per capita incomes either in the increase use of non-fossil fuel sources of energy, or in adapting innovative emission-reduction technologies, or in the relatively less energy-intensive service sector.

The impact of the 'oil shocks of the 1970s' upon the fuel-mix of a number of high-income economies was such that it has negated the otherwise strong relationships prevailed between the CO_2 emission of a country and her economic prosperity in high-income economies such as Austria, France, Japan, Sweden, and United States (Aldy, 2005; Friedl and Getzner, 2003; Lanne and Liski, 2004; Lindmark, 2002; Managi, 2006; Shanthini and Perera, 2007; Unruh and Moomaw, 1998).

In case of Australia, however, the place of fossil-fuel in its fuel-mix has been so strong that it has never fallen below 94% of the total energy consumption since 1965 (British Petroleum, 2009). In 2006, for instance, about 44% of Australia's total energy consumption was met by coal, 33.6% by petroleum, 19% by natural gas, 2.8% by hydroelectricity, and about 0.6% by other renewable energy sources (Energy Information Administration, 2008). It is therefore highly likely that the fossil-fuel based CO_2 emissions in Australia and her economic prosperity may move together describing a cointegrating relationship (Engle and Granger, 1987) between them.

The primary objective of this study is to seek for the probable existence of a cointegrating relationship between Australia's fossil-fuel based CO_2 emission per capita and her gross domestic product (GDP) per capita measured in market exchange rates, which is the proxy used for economic prosperity. In case of firmly establishing a cointegrating relationship, the next step is to develop a robust statistical model describing the long-run equilibrium relationship and the short-run dynamic equation prevailing between the emission per capita and GDP per capita for Australia. The existence of statistically significant long-run equilibrium relationship and short-run dynamic equation would pave the way for forecasting Australia's fossil-fuel based CO_2 emission per capita for hypothetical growth scenarios of her GDP per capita (Amarawickrama and Hunt, 2008).

The econometric methodology used is the cointegration testing procedure advocated in the autoregressive distributed lag (ARDL) bound-testing approach (Pesaran, Shin, and Smith, 2001). ARDL approach is adopted in this study since it is known to be better suited for regressors of different order of integration (Pesaran, Shin, and Smith, 2001) and for small sample sizes (Pesaran and Shin, 1999).

Cointegration is not new for the CO_2 emission versus income research literature. Friedl and Getzner (2003) showed evidence for the existence of cointegration between the Austrian annual emission and income time series in the range of 1960 to 1999. They used the augmented Dickey-Fuller test in the sense of Engle and Granger (1987) to arrive at the conclusion, and then reverted back to ordinary least square (OLS) regression approach to estimate the parameters of a simple linear model with a dummy variable accounting for structural break in 1974, of an EKC model, and of an 'N-shaped' model. Aldy (2005) tested for cointegration among the emission, income, and income-squared state-specific time series using the Engle-Granger type augmented Dickey-Fuller test for United States using the state-level annual data spanning 1960 to 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, and estimated the parameters of the EKC-type models of these states using the state-specific dynamic OLS regression. Both Friedl and Getzner (2003) and Aldy (2005), however, failed to complement their cointegration analyses with the standard equilibrium-correction modelling approach which combine the long-run equilibrium relationship with the short-run dynamic equation (Engle and Granger, 1987; Pesaran, Shin, and Smith, 2001).

In this paper, for the first-time to the best of our knowledge, the ARDL modelling approach has been employed to capture the long-run equilibrium relationship between the CO_2 emission and income time series. The rest of the paper is organized in the following manner. Time series data used for developing the model and their characteristics are presented in Section 2 along with the rationale behind the model developed. A brief account of the ARDL bound-testing approach used to develop the model is presented in Section 3. Section 4 presents the results and discussion and Section 5 concludes.

2 Data characteristics

2.1 Data used

Historic time series data on the Australian annual CO_2 emission estimates are available in two independent sources which are the Carbon Dioxide Information Analysis Center (Marland, Boden, and Andres, 2008), abbreviated CDIAC, and the International Energy Agency (2009), abbreviated IEA. CDIAC uses the 'Reference Approach' which is based on the supply of energy in a country and IEA uses the 'Sectoral Approach' which includes emissions only when the fuel is actually combusted (International Energy Agency, 2009, pp.31-32).

Figure 1 shows the cumulative CO_2 emissions stemming from the burning of solid, liquid and gaseous fossil fuel obtained from both sources. It is evident in Figure 1 that the emissions from the two sources somewhat differ from each other since 1980 and that a decline in emission during 1998 to 2001 has been reported by CDIAC and not by IEA. CDIAC emissions estimates are based on the fuel consumption data available in the Energy Statistics Database of United Nations Statistics Division, which reports a 9.2% decline in Australia's gross production of coal during 1998 to 1999 coupled with the 5.9% increase in her coal exports during the same period. This fact explains the decline in emission in 1998 reported by CDIAC (private communication with Tomas A. Boden, CDIAC Director). However, such decline in Australia's coal production has not been reported in any data sources of Australian origin or in the IEA database. It is therefore IEA data source was chosen as the primary emission data source of this study with the emission data from CDIAC added to cover the range of 1960 to 1973.

The CO_2 emission per capita time series data used in this study were derived from dividing the aforementioned CO_2 emission data by the mid-year population data obtained from World Development Indicators (World Bank, 2008). Time series data on the Australian annual GDP per capita were obtained from the same source as well. Unit of CO_2 emission per capita used in this study is tonne of CO_2 (which is equivalent to 1000 kg of CO_2) and that of GDP per capita is thousand of constant 2000 US$. It can be observed in Figure 2 that the data used for model development, spanning the period 1960 to 2007, exhibit a tendency to move together suggesting the probable existence of a cointegrating relationship between CO_2 emissions per capita and GDP per capita. It is also to be noted in Figure 2 that both the CO_2 emissions per capita growth and the GDP per capita growth slow down during the 1970s, which is the decade of two major oil shocks, and that the emission appear to flatten out since 2000.

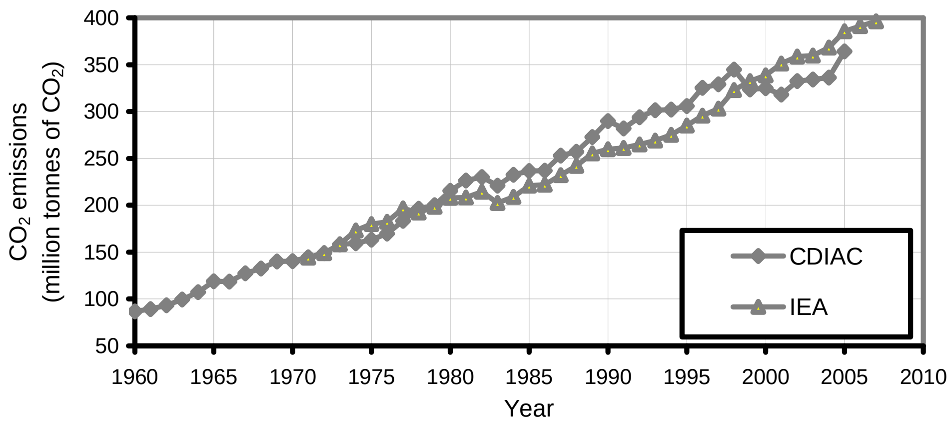

Figure 1 Australia's estimated annual carbon dioxide emissions stemming from the burning of solid, liquid and gaseous fossil fuel, obtained from CDIAC (Carbon Dioxide Information Analysis Center) and IEA (International Energy Agency).

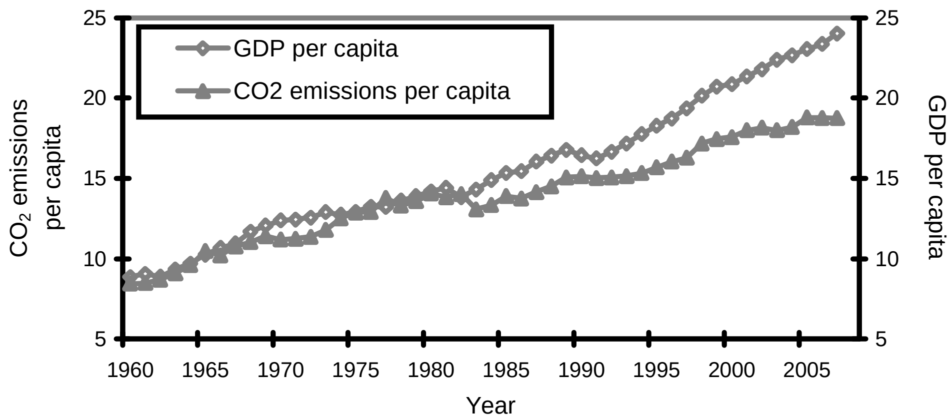

Figure 2 Australia's annual carbon dioxide emission per capita (in tonnes of CO_2) and her annual GDP per capita (in thousands of constant 2000 US$).

Figure 3 shows that the annual average marker crude oil price (British Petroleum, 2009) experienced very little fluctuations till 1973, then a sharp increase during 1973 to 1974, and another increase during 1978 and 1979. This decade of two major oil shocks is followed by a general decline in oil price till 1998. From 1998 to 2008, oil price has increased once again.

The impact of the oil shock decade on Australian CO_2 emission is such that the percentage shares of CO_2 emissions stemming from coal and oil burning switched their roles (Figure 4). Emission from oil burning has been on the decline and that from coal burning has been on the increase since the oil-shock decade. It is therefore the influence of oil price upon the relationship between CO_2 emissions per capita and GDP per capita is also researched into in this study.

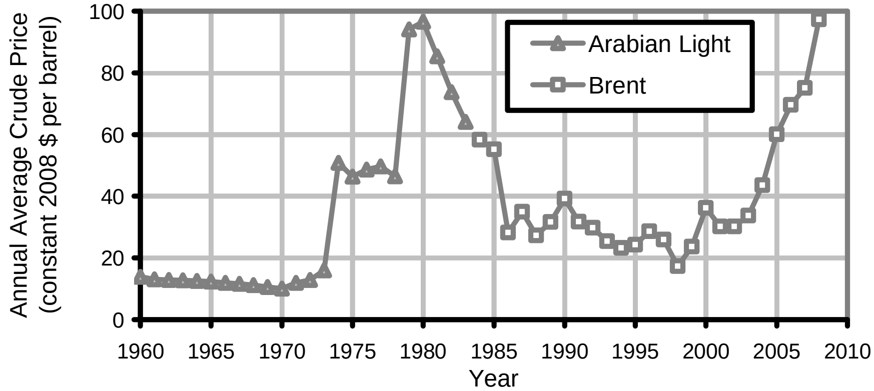

Figure 3

Figure 3 Variation in the marker crude price during 1960 to 2008.

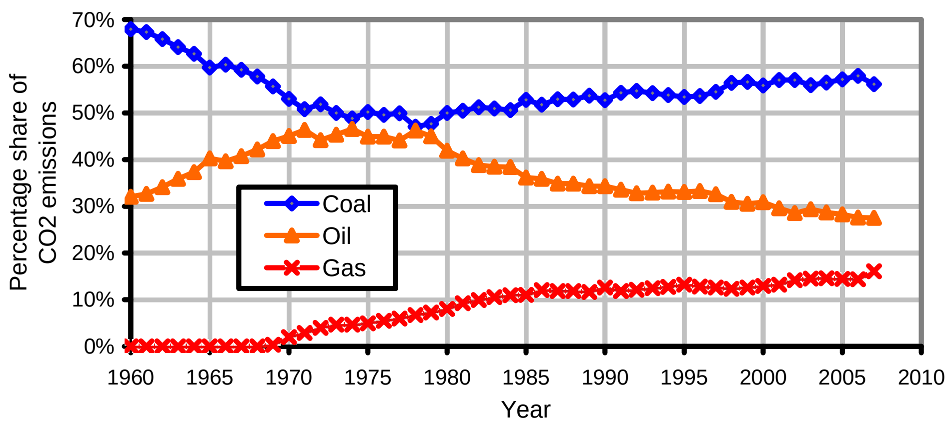

Figure 4 Percentage shares of carbon dioxide emissions stemming from burning of solid, liquid and gas fossil fuels.

2.2 Model rationale

The study of the data presented in Section 2.1 led us to hypothesize that there exists a cointegrating relationship between CO_2 emissions per capita and GDP per capita, and that these two variables must be strongly tied up in a long-run relationship. We also hypothesize that the inclusion of oil price might strengthen the long-run equilibrium relationship, even though the impact of oil price on CO_2 emissions per capita would be many folds smaller than the impact of GDP per capita on it. Since we are interested in the temporal growths of the variables concerned, we use natural logarithms of the variables for model development. Natural logarithms of CO_2 emissions per capita, GDP per capita, and oil price are denoted by $C(t)$, $G(t)$, and $O(t)$, respectively, where t represents the time in years.

2.3 Stationary tests

Since the landmark contribution of Engle and Granger (1987) in the regression analyses of time series, it has become a routine procedure to test if the time-series concerned are stationary or not. It is because an OLS regression model developed with non-stationary time series data violate the standard assumptions for asymptotic analyses such as hypothesis tests about the regression parameters (Granger and Newbold, 1974). Time series data on *C*, *G* and *O* were thus subjected to augmented Dickey-Fuller test (ADF), GLS-detrended Dickey-Fuller test (DF-GLS), Phillips-Perron test (PP), Ng and Perron test (NP-MZt), and Kwiatkowski, Phillips, Schmidt, and Shin test (KPSS) of Dickey and Fuller (1979), Elliott, Rothenberg, and Stock (1996), Phillips and Perron (1988), Ng and Perron (2001), and Kwiatkowski et al. (1992), respectively. All tests except the KPSS test have the null hypothesis that the data series tested contains a unit root, i.e. the tested series is non-stationary. The KPSS test has the null of the tested series being stationary. The test statistics obtained at levels and at first differences of *C*, *G* and *O*, using the statistical package EViews6 from Quantitative Micro Software LLC, are listed in Table 1. All test statistics confirm that *C* and *G* are non-stationary at level and stationary at first difference. That is, *C* and *G* are $I(1)$ series. All tests but the KPSS test point out that *O* is an $I(1)$ series. When considering the KPSS test statistics, *O* must be taken as an $I(0)$ series. Since *O* is used as a regressor in the ARDL procedure used in this study, whether *O* is an $I(1)$ series or an $I(0)$ series does not effect the analyses (Pesaran, Shin, and Smith, 2001).

Table 1 Unit root / Stationary test statistics for *C*, *G*, and *O* (which are the respective natural logarithms of CO_2 emissions per capita, GDP per capita, and oil price) and their first differences.

Variable	ADF test	DF-GLS test	PP test	NP-MZt test	KPSS test
C	-1.91 [0]	0.94 [0]	-2.06	2.48	0.73**
ΔC	-6.72 [0]***	-6.44 [0]***	-6.72***	-3.34***	0.27
G	-0.89 [0]	2.46 [0]	-0.86	4.52	0.74***
ΔG	-5.72 [0]***	-5.77 [0]***	-5.71***	-3.34***	0.13
O	-1.23 [0]	-0.85 [0]	-1.38	-0.90	0.29
ΔO	-6.47 [0]***	-6.39 [0]***	-6.48***	-3.41**	0.09

Note: Symbol Δ denotes first difference. Symbols *** and ** indicate significance at the 1% and 5% levels, respectively. Given within the brackets are the respective lag lengths of the ADF and DF-GLS test statistics, selected automatically based on Hannan-Quinn Criterion with the user specified maximum lag of 9. The PP, NP-MZt and KPSS test statistics are based on the automatically selected Newey-West bandwidth using Parzen kernel.

3 Econometric methodology

In the ARDL bound-testing approach (Pesaran and Shin, 1999; Pesaran, Shin, and Smith, 2001), testing of cointegration among a dependent variable Y and regressors X_j $(j = 1, 2, \ldots, k)$ begins with the unrestricted equilibrium correction model (ECM), given by Eq. (1), in which the regressors X_j may be $I(0)$ or $I(1)$ series.

$$\Delta Y(t) = \alpha_0 + \beta_y Y(t-1) + \sum_{j=1}^{k} \beta_j X_j(t-1) + \sum_{i=1}^{p} a_i \Delta Y(t\text{-}i) + \sum_{j=1}^{k} b_j \Delta X_j(t) + \sum_{i=1}^{p}\sum_{j=1}^{k} b_{ij} \Delta X_j(t\text{-}i) + \varepsilon(t) \qquad (1)$$

where Δ symbolizes the first difference, α_0 is the unrestricted intercept, β_y is the coefficient of the lagged level dependent variable Y and β_j $(j = 1, 2, \ldots, k)$ are the coefficients of the lagged level regressors X_j, t is time in year, a_i are the coefficients of lagged ΔY, b_j are the coefficients of current ΔX_j, b_{ij} are the coefficients of lagged ΔX_j, k denotes the maximum number of regressors used, p denotes the maximum lag length used, and $\varepsilon(t)$ are the serially uncorrelated residuals.

The first step in the ARDL bound testing approach is to determine the optimal value for the lag length p in Eq. (1) so as to maintain the balance between mitigating the residual serial correlation problem in Eq. (1) and refraining from over-parameterizing Eq. (1). This is done by estimating Eq. (1) using the OLS procedure for different values of lag length p. For each regression, Akaike’s Information Criterion (AIC) is determined. The lag length corresponding to the regression with extreme value for AIC is chosen as the maximum lag length. The above choice is further fortified by the determination of the Breusch-Godfrey Lagrange multiplier test statistics for testing the null hypothesis of no residual serial correlation.

Having chosen the appropriate lag length p, the probable existence of a cointegrating relationship in Eq. (1) is tested in the ARDL bound-testing procedure by calculating the F-statistic under the null hypothesis that $\beta_y = \beta_j$ $(j = 1, 2, \ldots, k) = 0$ (that is, no cointegration) against the alternative hypothesis that they are not. The F-statistic is then compared with the asymptotic critical value bounds provided in Pesaran, Shin and Smith (2001) that are reproduced in Table 2 for the cases of (i) a single regressor and (ii) two regressors.

If the F-statistic falls on the right-hand side of the upper bound critical value then the null of no cointegration is rejected and cointegration among the variables is firmly established. Consequently, a long-run equilibrium relationship among the dependent variable Y and the regressors X_j shall be established in which the X_j are regarded as forcing Y. If the F-statistic falls on the left-hand side of the lower bound critical value then the null cannot be rejected and no cointegration among the variables is firmly established. Finally, if the F-statistic falls between the lower and upper bound critical values, no conclusive decision could be reached.

Table 2 Asymptotic critical value bounds for F-statistic and t-ratio at 5% level of significance for the cases of (i) a single regressor and (ii) two regressors.

Test statistic	Asymptotic critical value bounds at 5% level of significance			
	(i) with a single regressor		(ii) with two regressors	
	Lower bound $I(0)$	Upper bound $I(1)$	Lower bound $I(0)$	Upper bound $I(1)$
F_{III}	4.94	5.73	3.79	4.85
t_{III}	-2.86	-3.22	-2.86	-3.53

Note: F_{III} is the F-statistic for testing $\beta_y = \beta_j$ $(j = 1, 2, \ldots, k) = 0$ in Eq. (1) and t_{III} is the t-ratio for testing $\beta_y = 0$ in Eq. (1). Critical values for F_{III} and t_{III}, are obtained from Tables CI(iii), and CII(iii) of Pesaran, Shin and Smith (2001), respectively.

The above test is complemented by the calculation of *t*-ratio under the null hypothesis of $\beta_y = 0$ in Eq. (1) against the alternative hypothesis that it is not. The *t*-ratio is then compared with the asymptotic critical value bounds tabulated in Table 2. If the *t*-ratio falls on the right-hand side of the upper bound critical value then the null of $\beta_y = 0$ is rejected. If it falls on the left-hand side of the lower bound critical value then the null cannot be rejected. If it falls within the bounds then no conclusive decision could be reached.

Once the non-rejection of cointegration among the variables concerned are established, the long-run equilibrium relationship is estimated using the ARDL approach detailed in Pesaran and Shin (1999). First, the numerical values of the lag orders m and n_j $(j = 1, 2, \ldots k)$ of the $ARDL(m,n_j)$ model, expressed by Eq. (2), are estimated using the OLS procedure for different combinations of m and n_j $(j = 1, 2, \ldots k)$.

$$Y(t) = \sigma_0 + \sum_{i=1}^{m} \gamma_i Y(t\text{-}i) + \sum_{j=1}^{k} \sum_{i=0}^{n_j} \tau_{ij} X_j(t\text{-}i) + \upsilon(t) \tag{2}$$

where σ_0 is the constant term, γ_i are the coefficients of the lagged level dependent variable Y, τ_{ij} are the coefficients of the current and lagged level regressors X_j, k denotes the maximum number of regressors used, m and n_j denote the maximum lag lengths of Y and X_j, respectively, and $\upsilon(t)$ are the serially uncorrelated residuals.

The lag lengths corresponding to the regression with minimum value for AIC or for Schwarz Criterion (SC) give the $ARDL(m,n_j)$ model representing the long-run equilibrium relationship. The coefficients of the long-run equilibrium relationship are estimated using the OLS procedure, and the corresponding standard errors and *t*-statistics are estimated using the Delta method as suggested in Pesaran and Shin (1999).

The residuals of the long-run equilibrium relationship is known as the equilibrium correction term, which paves the way for estimating the short-run dynamic equation among Y and X_j by setting up a conditional ECM corresponding to the $ARDL(m,n_j)$ model representing the long-run equilibrium relationship. In the conditional ECM, the first difference of Y is regressed on a one period lag of the equilibrium correction term, lagged first differences of Y and current and lagged first differences of X_j using OLS regression (Pesaran, Shin, and Smith, 2001).

The short-run dynamic equation is considered statistically significant only if the residuals of the model do not reject the null hypotheses of no residual serial correlation, no heteroskedasticity among the residuals, and normally distributed residuals. These hypotheses tests were carried out in this study using the Breusch-Godfrey Lagrange multiplier test, Jarque-Bera normality test, and ARCH heteroskedasticity test, respectively. The stability of the estimated parameters of the short-run dynamic equation is tested by employing the Ramsey regression specification error test (RESET), which would reveal any misspecification in the short-run dynamic equation such as non inclusion of all relevant variables. The stability was further verified using the cumulative sum of recursive residuals (CUSUM) test (Brown, Durbin, and Evans, 1975).

4 Results and discussion

4.1 Cointegration test results

Cointegration was first tested with C as the dependent variable and G as the regressor. Eq. (1) with $k = 1$ was estimated using the OLS regression for different values of lag length p. Since a limited number of annual data were used for the analyses, maximum value of p was limited to 3. For each regression, AIC statistics, P-values of Breusch-Godfrey Lagrange multiplier test statistics at prescribed lag orders 1 and 4, F-statistic, and t-ratio were estimated. All statistics, except the AIC statistics, for the cases of p = 0, 1, 2, and 3 were evaluated using the data sets spanning the periods 1961-2007, 1962-2007, 1963-2007, and 1964-2007, respectively. In estimating the AIC statistics for all values of p, the data set spanning the period 1964-2007 was used, which was a necessity to aid comparison among the AIC values estimated.

The results, tabulated in Table 3, show that the AIC statistic is at its minimum at p = 3. The corresponding P-values of the Breusch-Godfrey Lagrange multiplier test statistics are large enough to not reject the null hypothesis of no residual serial correlation even at 10% level of significance. The corresponding F-statistic listed in Table 3 falls on the right-hand side of the respective upper bound critical value (listed in Table 2) resulting in the rejection of the null of no cointegration at 5% level of significance. The t-ratio given in Table 3 reveals that the null of $\beta_y = 0$ in Eq. (1) is also rejected at 5% level of significance. It is therefore the existence of cointegration among the variables C and G for Australia is strongly established with G forcing C. That is, GDP per capita forces CO_2 emissions per capita.

Table 3 Statistics for testing the existence of a cointegrating relationship between C and G in Eq. (1) with k = 1, with C as the dependent variable and G as the regressor.

Maximum lag length	$p = 0$	$p = 1$	$p = 2$	$p = 3$
AIC	-4.545	-4.522	-4.436	-4.726
Probability $\chi^2_{SC}(1)$	0.605	0.493	0.564	0.375
Probability $\chi^2_{SC}(4)$	0.667	0.761	0.038	0.404
F_{III}	6.48^{right}	5.49^{mid}	6.21^{right}	8.32^{right}
t_{III}	-3.27^{right}	-2.77^{left}	-3.02^{mid}	-3.96^{right}

Note: Probability $\chi^2_{SC}(1)$ and Probability $\chi^2_{SC}(4)$ denote the P-values of the Breusch-Godfrey Lagrange multiplier test statistics for the null of no residual serial correlation at pre-specified lag orders 1 and 4, respectively. Superscripts ^{right}, ^{left}, and ^{mid} denote that the statistic concerned falls on the right-hand side of the upper critical bound, on the left-hand side of the lower critical bound, and in the middle of the critical bounds tabulated in Table 2, respectively.

When the above analyses were repeated with G as the dependent variable and C as the regressor, the F-statistics and t-ratios of all cases studied fell on the left-hand side of the respective lower bound critical values, and thereby resulting in the non-rejection of the null of no cointegration. It can therefore be concluded that, in case of Australia, GDP per capita forces CO_2 emissions per capita and CO_2 emissions per capita does not force GDP per capita.

The results of the tests carried out in search of a cointegration relationship among C, G and O with C as the dependent variable, tabulated in Table 4, show that p = 3 was chosen. However, the corresponding F-statistic and t-ratio fall within the critical bound values (listed in Table 2) resulting in neither the rejection nor the non-rejection of the null of no cointegration at 5% level of significance. It is therefore the existence of a long-run relationship among *C*, *G* and *O* for Australia is not firmly established.

Table 4 Statistics for testing the existence of a cointegrating relationship among *C*, *G* and *O* in Eq. (1) with $k = 2$, with *C* as the dependent variable and *G* and *O* as the regressors.

Maximum lag length	$p = 0$	$p = 1$	$p = 2$	$p = 3$
AIC	-4.571	-4.541	-4.417	-4.627
Probability $\chi^2_{SC}(1)$	0.498	0.247	0.853	0.395
Probability $\chi^2_{SC}(4)$	0.849	0.473	0.060	0.352
F_{III}	4.48^{mid}	4.27^{mid}	4.36^{mid}	4.84^{mid}
t_{III}	-3.06^{mid}	-2.74^{low}	-2.82^{low}	-3.05^{mid}

Note: Same as in Table 3.

4.2 Long-run equilibrium relationships

Since cointegration between the dependent variable *C* and the forcing variable *G* was firmly established, as discussed in Section 4.1, as the next step, the long-run equilibrium relationship between *C* and *G* was estimated. First the AIC and SC statistics were estimated for different combinations of the lag orders *m* and n_1 in the $ARDL(m,n_1)$ model, given by Eq. (2) with $k = 1$. Since we deal with annual data, the maximum lag length was limited to 3. We therefore carried out 16 (= $[3+1]^2$) regressions. Of which, the minimum AIC value was found to correspond to the *ARDL*(*1,2*) model whereas the minimum SC value corresponded to the *ARDL*(*1,0*) model. The coefficients of the levels relationship given by the *ARDL*(*1,2*) and *ARDL*(*1,0*) models were estimated using the OLS procedure, and the corresponding standard errors and *t*-statistics were estimated using the Delta method. The results are tabulated in Table 5.

Table 5 shows that the coefficients and the standard errors of the *ARDL*(*1,2*) and *ARDL*(*1,0*) models are very similar, and therefore the *ARDL*(*1,2*) model is chosen to represent the long-run equilibrium relationship between *C* and *G*, and is expressed by Eq. (3).

$$ARDL(1,2):\quad C(t) = \underset{[5.1]}{0.7468} + \underset{[13.5]}{0.7020}G(t) + \hat{v}_1(t) \qquad (3)$$

where the numerical values given within the brackets are the *t*-statistics of the corresponding coefficients and the residual $\hat{v}_1(t)$ is the equilibrium correction term.

Table 5 Coefficients and related statistics of the long-run equilibrium relationship between *C* and *G*.

Regressor	Coefficient	Standard Error	t-statistic
ARDL(*1,2*):			
Constant	0.7468	0.1473	5.07
G	0.7020	0.0519	13.5
ARDL(*1,0*):			
constant	0.7070	0.1517	4.66
G	0.7202	0.0525	13.73

Since the null of no cointegration among the dependent variable *C* and the forcing variables *G* and *O* was not rejected, as discussed in Section 4.1, the long-run equilibrium relationship between *C*, *G* and *O*, given by Eq. (4), was also estimated following a procedure similar to that described in the preceding paragraphs.

$$ARDL(1,2,0):\quad C(t) = \underset{[7.2]}{0.6399} + \underset{[19.6]}{0.6842}G(t) + \underset{[2.8]}{0.0396}O(t) + \hat{v}_2(t) \qquad (4)$$

where the *t*-statistics are given within the brackets below the corresponding coefficients and the residual $\hat{v}_2(t)$ is the equilibrium correction term.

The *t*-statistics in Eq. (3) and (4) prove that the coefficients of the forcing variables *G* and *O* are statistically significant. Moreover, the long-run equilibrium relationships show that 1% increase in GDP per capita causes about a 0.7% increase in CO_2 emissions per capita, whereas 1% increase in oil price causes only an insignificant 0.04% increase in CO_2 emissions per capita.

4.3 Short-run dynamic equations

The short-run dynamic equation estimated from the conditional ECM corresponding to *ARDL*(*1,2*), using the OLS procedure, is given in Table 6 along with the estimated essential statistics. It is evident from the tabulated results that the coefficient of the equilibrium correction term $\hat{v}_1(t-1)$, known as the adjustment parameter, not only has the expected negative sign, but also is highly significant, which can be taken as further proof of the existence of a stable long-run equilibrium relationship (Bannerjee, Dolado, and Mestre, 1998). The numerical value of the adjustment parameter reveals that any deviation from the long-run equilibrium following a short-run disturbance is corrected by about 36% in a year. Tabulated P-values also show that the coefficient of $\Delta G(t\text{-}1)$ is statistically significant at 10% level and that the coefficients of $\Delta G(t)$ and $\Delta G(t\text{-}2)$ must be taken as zero. Therefore, we conclude that the impact of GDP per capita growth upon the CO_2 emissions per capita growth is such that 1% increase in the GDP per capita growth in the previous year would lead to about 0.33% increase in the CO_2 emissions per capita growth in the current year.

Table 6 Equilibrium correction form of the *ARDL(1,2)* model of Eq. (3).

Regressor	Coefficient	Standard Error	t-Statistic	P-value
$\hat{v}_1(t-1)$	-0.3640	0.0947	-3.84	0.0004
$\Delta G(t)$	-0.0116	0.1634	-0.07	0.9439
$\Delta G(t\text{-}1)$	0.3247	0.1768	1.84	0.0736
$\Delta G(t\text{-}2)$	-0.0772	0.1570	-0.49	0.6256

adjusted R^2 = 32.4%; Durbin-Watson statistic = 2.06

$\chi^2_{SC}(4)$ = 3.45 [0.49]; $\chi^2_N(2)$ = 0.49 [0.78]; $\chi^2_H(1)$ = 0.24 [0.62]; $\chi^2_{FF}(1)$ = 1.79 [0.18]

Note: The equilibrium correction term $\hat{v}_1(t-1)$ is the residual of Eq. (3). $\chi^2_{SC}(4)$, $\chi^2_N(2)$, $\chi^2_H(1)$ and $\chi^2_{FF}(1)$ denote chi-squared statistics of Breusch-Godfrey serial correlation LM test, Jarque-Bera normality test, ARCH heteroskedasticity test, and RESET, respectively. The corresponding P-values are given within the brackets.

P-values corresponding to the chi-squared statistics of the residual tests, tabulated in Table 6, show that none of the test statistics was significant even at 10% level of significance. We therefore concluded that the parameter estimates of the short-run dynamic equation are statistically significant. P-values corresponding to the RESET ruled out any model misspecification in the short-run dynamic equation.

In order to further verify the stability of the short-run dynamic equation, we subjected it to the CUSUM test. Figure 5 reveals that CUSUM confines itself within the 5% critical lines and that the departure of CUSUM from the zero line is insignificant since 1980. It is therefore we conclude that the estimated coefficients have remained nearly constants from one sample period to the other providing further verification for the stability of the short-run dynamic equation considered.

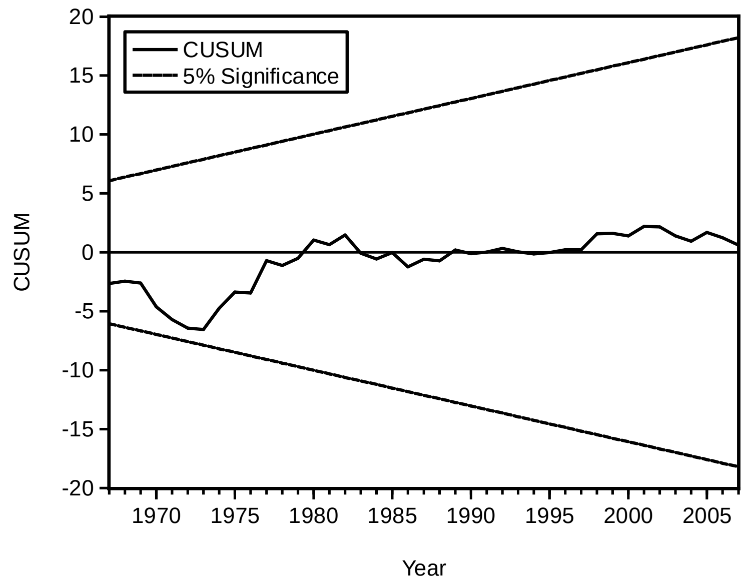

Figure 5 Cumulative sum of recursive residuals (CUSUM) of the conditional ECM given in Table 6. The broken lines represent the 5% critical limit.

The short-run dynamic equation estimated from the conditional ECM corresponding to *ARDL*(*1,2,0*) is given in Table 7. The adjustment parameter is highly significant and its numerical value reveals that any deviation from the long-run equilibrium following a short-run disturbance is corrected by about 51% in a year. Moreover, the coefficient of $\Delta G(t\text{-}1)$ is statistically significant at 5% level, the coefficients of $\Delta G(t)$ and $\Delta G(t\text{-}2)$ must be taken as zero, and the coefficient of $\Delta O(t)$ is statistically significant at 10% level,. Therefore, we conclude that 1% increase in the GDP per capita growth in the previous year would lead to about 0.33% increase in the CO_2 emissions per capita growth in the current year and that 1% increase in the growth in oil price would lead to a negligible 0.02% increase in the CO_2 emissions per capita growth in the same year. The P-values corresponding to the chi-squared statistics confer statistical significance of the parameter estimates of the short-run dynamic equation considered as well as the absence of any model misspecification.

Table 7 Equilibrium correction form of the ARDL(1,2,0) model of Eq. (4).

Regressor	Coefficient	Standard Error	t-Statistic	P-value
$\hat{v}_2(t-1)$	-0.5109	0.1205	-4.24	0.0001
$\Delta G(t)$	0.1364	0.1528	0.89	0.3773
$\Delta G(t\text{-}1)$	0.3353	0.1651	2.03	0.0489
$\Delta G(t\text{-}2)$	0.0560	0.1476	0.38	0.7064
$\Delta O(t)$	0.0230	0.0121	1.90	0.0642

adjusted R^2 = 38.9%; Durbin-Watson statistic = 1.88

$\chi^2_{SC}(4)$ = 4.59 [0.33]; $\chi^2_N(2)$ = 0.55 [0.76]; $\chi^2_H(1)$ = 0.019 [0.89]; $\chi^2_{FF}(1)$ = 0.17 [0.68]

Note: The equilibrium correction term $\hat{v}_2(t-1)$ is the residual of Eq. (4). Chi-squared statistics are described in Table 6.

4.4 CO_2 emissions forecast

From the results presented in the preceding three subsections, it could be firmly concluded that there exists a strong cointegrating relationship between CO_2 emissions per capita and GDP per capita and that the impact of oil price on CO_2 emissions per capita is negligible. Therefore, for forecasting purposes, we would consider only the long-run equilibrium relationship given by Eq. (3) and the corresponding short-run dynamic equation given in Table 6. Subjecting the latter for further statistical testing, we find that it has a Theil inequality coefficient of 0.39 in the scale of 0, indicating perfect fit, to 1. The bias and the variance proportions of the mean squared forecast error were estimated to be 0.0015 and 0.2075, respectively. The near zero bias proportion indicates that the mean of the forecast is exactly the same as the mean of the actual series, and the 21% variance proportion indicates that there is only a very small difference between the variations of the forecast and of the actual series. Such small bias and variance proportions testify the forecasts of the short-run dynamic equation considered are reliable.

The forecast equation is derived by substituting the equilibrium correction term from the long-run equilibrium relationship given by Eq. (3) into the corresponding short-run dynamic equation given in Table 6 as follows:

$$\Delta C(t) = -0.3640\left[C(t\text{-}1)\text{-}0.7020G(t\text{-}1) - 0.7468\right] + 0.3247\Delta G(t-1) \qquad (5)$$

Figure 6 shows the CO_2 emissions per capita obtained by dynamically simulating Eq. (5), along with the actual co2pc values used for developing the model. Dynamical simulation of Eq. (5) is carried out with the actual values of GDP per capita and with the actual value of CO_2 emissions per capita at 1960 as the initial emission input. The match between the model predictions and the actual emissions seen in Figure 6 is commendable. Eq. (5) could therefore be used for reliably forecasting Australia's future CO_2 emissions.

In forecasting CO_2 emissions per capita after 2007, which is the end year of the data set used, we used four different hypothetical GDP per capita growth rate scenarios, which were the low-growth, reference-growth, average-growth, and high-growth scenarios. In these scenarios, GDP per capita was assumed to grow at the rates of 0.7%, 1.4%, 2.5%, and 4.1%, respectively, from 2007 onwards. The low, average and high GDP per capita growth rates were the respective minimum, average and maximum GDP per capita growth rates prevailed during the period 1992-2007. The reference growth scenario assumes current trends in economic activity continue into the future (Commonwealth of Australia, 2008, pp.17).

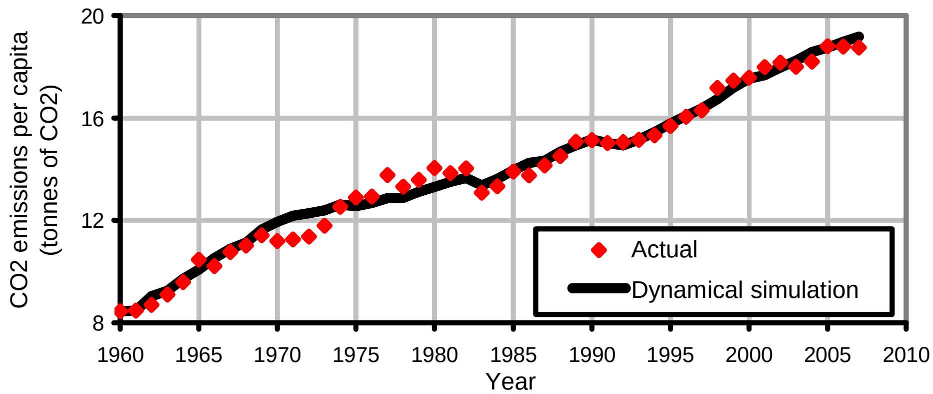

Figure 6 Dynamically simulated CO_2 emissions per capita using the forecast equation, Eq. (5), compared with the actual values used for model development.

Forecasts of cumulative CO_2 emissions in 2010, 2020 and 2030 were calculated by multiplying the forecasted CO_2 emissions per capita values for these years by the respective medium variant population projections of United Nations (2009), which were 21,512,000 in 2010, 23,675,000 in 2020, and 25,656,000 at 2030, respectively. The results are tabulated in Table 8.

Gurney et al. (2007) observed that in the absence of any major regional or global climate change initiatives and without any significant technological breakthroughs, greenhouse gas (GHG) emissions in Australia would reach 549, 638, and 695 million tonnes of CO_2 equivalent in 2010, 2020, and 2030, respectively. The composition of CO_2 emissions in the total GHG emissions of Australia was about 70% in 1990 (Australian Bureau of Statistics, 2007) and about 74% on 2005 (Australian Bureau of Statistics, 2007). If this composition is assumed to vary in the range of 74% to 80% during 2010 to 2030, the CO_2 emissions would fall in the range of 406 to 439 million tonnes of CO_2 in 2010, 472 to 510 million tonnes of CO_2 in 2020, and 514 to 556 million tonnes of CO_2 in 2030.

Table 8 Forecast of cumulative CO_2 emissions stemming from the burning of solid, liquid and gaseous fossil fuel at hypothetical growth rates of GDP per capita since 2007 and at United Nations predicted medium variant population projections.

Hypothetical scenario	GDP per capita growth rate since 2007 (in %)	Fossil-fuel based CO_2 emissions projection (in million tonnes of CO_2)		
		2010	2020	2030
Low-growth	0.7	425	492	560
Reference-growth	1.4	429	521	622
Average-growth	2.5	434	568	732
High-growth	4.1	443	644	925

Retuning to the results tabulated in Table 8, it could be seen that the projected CO_2 emissions in 2010 for the low, reference and average-growth scenarios fall in the range of 406 to 439 million tonnes of CO_2. Projected CO_2 emission in 2020 falls in the range of 472 – 510 million tonnes of CO_2 only in the low-growth scenario. Projected CO_2 emission in 2030 is slightly larger than 556 million tonnes of CO_2 in the low-growth scenario. As it is highly likely that the GDP per capita growth rate of Australia during 2008 to 2030 lie below the reference-growth rate considered in this study, we conclude that the CO_2 emissions forecasts made by the model developed are comparable with the emissions predicted by Gurney et al. (2007).

The cumulative CO_2 emissions stemming from the burning of solid, liquid and gaseous fossil fuel in 2000 was 337 million tonnes of CO_2. Percentage growths in cumulative CO_2 emissions at 2010, 2020 and 2030 over 2000 level would, therefore, become 26%, 36%, and 46%, respectively, for the low-growth scenario and 27%, 40% and 55%, respectively, for the reference-growth scenario. It should be borne in mind that such high forecasted percentage increases of CO_2 emissions over the 2000 level would be realized only if the economic growth and energy consumption paths pursued by Australia since 1960 undergo no appreciable changes in the future.

5 Conclusion

Existence of a strong cointegrating relationship between Australia's CO_2 emission per capita and her GDP per capita is firmly established in this study. It is also proven that growing GDP per capita forces the CO_2 emissions per capita to grow, whereas the reverse is not true. Inclusion of oil price as a forcing variable is found to have insignificant impact on CO_2 emissions per capita which is not surprising because of the persistent high place of fossil-fuel in her fuel-mix owing to perhaps her indigenous fossil-fuel reserves.

In the long-run, 1% increase in Australia's GDP per capita causes about 0.7% increase in her CO_2 emission per capita. In the short-run, 1% increase in GDP per capita growth in the previous year leads to about 0.33% increase in the current growth in CO_2 emission per capita. Moreover about 36% of any deviation from the long-run equilibrium is corrected within a year. These results clearly prove that Australia's current economic development path is CO_2 emission intensive.

Such a strong tie between income and CO_2 emissions results in the projection of the cumulative CO_2 emissions stemming from the burning of solid, liquid and gaseous fossil fuel to grow by 36 to 40% in 2020 over the 2000 level for GDP per capita growth rates in the range of 0.7 to 1.4%. It should be borne in mind that such high forecasted percentage increases in CO_2 emissions would become a reality only in the absence of proactive actions taken by the Australian government to weaken the strong cointegrating relationship existing between CO_2 emissions and economic prosperity, measured by GDP per capita.

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