The determinants of CO2 emissions: empirical evidence from Italy

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Abstract

This paper investigates major determinants of CO2 emissions in a small open economy such as Italy over the period 1960-2012 using Granger causality and cointegration methods to ascertain short-run and long-run relationships between emissions, trade openness and energy consumption. The research findings do not support a possible decoupling between economic growth and energy consumption, so that energy conservation policies are expected to have a negative impact on economic growth. Therefore, the use of environmentally friendly and renewable energy sources, such as solar, hydro and wind power, should be further encouraged instead of fossil fuels ones.

JEL classification codes: F18, Q4, Q5

Keywords: Emissions, energy-GDP relationship; energy policy; cointegration; Italy

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Highlights

►CO2 emissions, economic growth, trade openness and energy consumption are cointegrated

►Economic growth is a strong and positive driver of emissions in the short-run

►Support for feedback hypothesis between economic growth and energy consumption in both the short-run and long-run

►Granger causality running from emissions to economic growth and energy consumption, but no evidence of reverse causality

►Energy conservation policy will reduce economic growth

1. Introduction

The environmental impact of economic activities has received increasing attention from academics and researchers, politicians and the society all together in recent decades. The wide use of fossil fuels has been one of the most important stimuli of economic growth. The nexus between pollution and economic development and the use of natural resources has been explained by the environmental Kuznets curve which hypothesizes an inverted-U relationship between pollution and economic development (Kuznets, 1955). Initially, when a country's per capita income is low environmental degradation will increase, but may decline with higher per capita income over time. Or, in other words, environmental pressure increases faster at early stages of development and then slows down relative to economic growth at higher levels of development. Environmental degradation might even be reduced in absolute terms.

The literature argues from an empirical point of view that there are three streams of research looking at the link between economic growth and environmental pollution. The first strand explores the relationship between economic growth and environment degradation by testing the validity of the environmental Kuznets curve hypothesis. Empirical evidence has not yet reached a consensus (Agras and Chapman, 1999; Dinda, 2004; Friedl and Getzner, 2003; Grossman and Krueger, 1995; Kearsley and Riddel, 2010; Liu, 2005; Selden and Song, 1994; Stern et al., 1996; Suri and Chapman, 1998). The second stream of research explores the relationship between economic growth and energy consumption (Akarca and Long, 1980;Kraft, 1978; Yu and Hwang, 1984). To infer the relationship between economic growth and environmental pollution, empirical studies make out that economic growth and energy consumption are in close relation to each other. Granger causality analysis with cointegrated variables applied to bivariate regression models (Bentzen and Engsted, 1993; Ghali and El-Sakka, 2004) and multivariate analysis (Apergis and Payne, 2009b; Lee, 2005; Soytas and Sari, 2003) appear to dominate this literature that aims at identifying the direction of both short-run and long-run causality in the relationship between the two variables. Overall, the specifications of econometric models have suffered from omitted variable bias yielding mixed results (Ozturk, 2010; Payne, 2010a, b). A third stream of research has emerged which combines the previous two strands by examining dynamic relationships between economic growth, energy consumption and pollution emissions (Apergis and Payne, 2009a, 2010; Martínez-Zarzoso and Maruotti, 2011; Omri, 2013; Poumanyvong and Kaneko, 2010; Saboori et al., 2012; Sari and Soytas, 2007; Shahbaz et al., 2013; Wang et al., 2011). Growing concern over climate change has given rise to a new literature, mainly panel-based research, devoted to investigate linkages between economic growth, energy consumption and pollutant emissions. Many empirical studies posit a nonlinear quadratic relationship according to the environmental Kuznets hypothesis (Ang, 2007; Halicioglu, 2009; Ozturk and Acaravci, 2013). The empirical studies typically determine Granger causality in the short-run and long-run sense and somehow do not pay attention to the measurement of the size and direction of short-term and long-term parameters among the variables of interest. As the literature stands, the research provides significant evidence on the drivers of CO2 emissions for a larger set of countries such as industrialized and newly industrialized countries, emerging economies and less regarding small open economies within a single-country setting (Ang, 2008; Apergis and Payne, 2009a; Chandran and Tang, 2013; Ozturk and Acaravci, 2010; Shahbaz et al., 2011; Sharma, 2011; Soytas et al., 2007; Zhang and Cheng, 2009).

As far as Italy is concerned, the empirical evidence is firmly based on multi-country studies applying panel unit root, panel cointegration, and panel causality techniques. Total energy consumption has a statistically significant impact on economic growth (Huang et al., 2008; Narayan et al., 2010). One study finds a unidirectional long-run causality running from GDP per capita to energy consumption per capita (Lee and Chang, 2007), whereas another a reversed relationship (Lee, 2006). Another study that exclusively examines the long-run relationship between energy consumption and real GDP finds a bidirectional causal relationship between these two variables (Belke et al., 2011). In contrast, there is only bidirectional short-run causality and unidirectional long-run causality from energy consumption to economic growth (Acaravci and Ozturk, 2010). Moreover, a study finds a reciprocal causal relationship among real income, real energy price, and total energy consumption, and a unidirectional causality running from income and electricity price to electricity consumption (Lee and De Lee, 2010). The results for the panel as a whole suggest that the demand for total energy and electricity in the OECD countries is driven largely by strong economic growth, while consumers are largely insensitive to price changes. On top of that, further empirical results suggest bidirectional causality between primary energy consumption and real GDP in both the long-run and short-run, supporting the feedback hypothesis (Fuinhas and Marques, 2012). Focusing on electricity consumption, some scholars find evidence in favour of electricity consumption causing real GDP in Italy without being able to identify any causal relationship (Narayan and Prasad, 2008).

The aforementioned studies have primarily based their findings on cointegration analysis and mainly on multi-country evidence. It is somehow surprising to observe that these papers report separate results for Italy. Although the Italian economy has a relatively small energy market and limited domestic energy resources, the rapid increase in the service-based sectors have placed significant pressure on energy consumption in the past years. Italy has a strong industrial basis and is highly dependent on fossil fuels so that the reduction of CO2 emissions represents a serious environmental challenge for this economy. Therefore, the question on how energy conservation may be viable without being detrimental to economic growth might be re-examined with time-series data to discuss differences in results for the case of Italy. Moreover, it is noticeable that the primarily goal of the published literature has not been on examining the drivers of pollutant emissions, and therefore estimating the size and direction of short-run and long-run parameters is of interest. This paper is a contribution attempting to partly fill these empirical and policy related gaps.

The remainder of the paper is structured as follows. Section 2 presents the econometric model, along with the data and the methods of estimation. Section 3 reviews and discusses the main empirical findings. Section 4 concludes and suggests further research directions.

2. Model and conceptual framework

This study uses annual data series expressed in 2005 constant US dollars for a fifty three years period from 1960 to 2012. Time series are collected from the World Bank, *World Development Indicators* (WDI) database 2013. Consider the following model specification:

$$CO2_t = f(Y_t, T_t, E_t) \tag{1}$$

Equation (1) is estimated in natural logarithmic form as follows:

$$lnCO2_t = \beta_0 + \beta_1 lnY_t + \beta_2 lnT_t + \beta_3 lnE + \varepsilon_t \tag{2}$$

where $CO2_t$ are CO2 emissions in kt, Y_t is economic growth proxy by the GDP in US dollars valued at constant 2005 prices, T_t is the openness to trade (sum of exports and imports as a share of GDP), and E_t is the energy consumption in kt oil equivalent. The equations above will be used to test the following three hypotheses:

H1: *Economic growth has a positive effect on CO2 emissions*. Theoretical and empirical literature has shown that higher levels of energy consumption are accompanied with higher levels of economic growth (Dinda and Coondoo, 2006; Wolde-Rufael, 2009).

H2: *Trade openness is expected to have a positive or a negative effect on CO2 emissions*. According to the standard Heckscher-Ohlin-Samuelson factor endowments model and international trade theory, countries specialize in the production of goods in which they possess a comparative advantage in factors of production such as capital and labour. Due to greater trade openness, countries trade and move goods produced with each other either to consume or to further process them. Pollution is then encouraged by the

production of more manufacturing goods. However, trade openness can reduce pollution (Antweiler et al., 2001; Hossain, 2011). Evidence for the impact of trade openness on pollution is mixed. Hence, the expected sign of this variable is ambiguous.
H3: *Energy consumption has a positive effect on CO2 emissions*. We expect that a higher consumption of energy, as required for economic growth, will rise the amount of CO2 emissions (Soytas and Sari, 2009).

According to the economic literature, cointegration and error correction modelling investigate and measure common long run path and short run effects among the variables of interest. Before starting any cointegration analysis, it is always necessary to ascertain the stationarity proprieties of the data series with tests of unit roots. This study employs the Augmented Dickey-Fuller ADF stationarity test, the more robust Phillips-Perron PP test, and the Kwiatkowski–Phillips–Schmidt–Shin KPSS test for stationarity (Dickey and Fuller, 1979; Kwiatkowski et al., 1992; Phillips and Perron, 1988). Cointegration analysis per se is carried out with the bounds testing approach to cointegration (Pesaran et al., 2001). This method involves estimating the Autoregressive distributed lag model (ARDL). It is a dynamic model that is consistently estimated by ordinary least squares and can be used with variables that are integrated of mixed order, i.e. one or lower. To investigate the presence of a long run equilibrium relationship among the variables, the following unrestricted autoregressive distributed lag models are estimated:

$$\begin{aligned} ln\Delta CO2_t = \alpha_0 &+ \delta_1 lnCO2_{t-1} + \delta_2 lnY_{t-1} + \delta_3 lnT_{t-1} + \delta_4 lnE_{t-1} \\ &+ \sum_{j=1}^{k} \beta_{1j} \Delta lnCO2_{t-j} + \sum_{j=0}^{k} \beta_{2j} \Delta lnY_{t-j} + \sum_{j=0}^{k} \beta_{3j} \Delta lnT_{t-j} + \sum_{j=0}^{k} \beta_{4j} \Delta lnE_{t-j} \\ &+ \mu_{1t} \end{aligned} \tag{3}$$

$$\begin{aligned} ln\Delta Y_t = \alpha_1 &+ \delta_1 lnCO2_{t-1} + \delta_2 lnY_{t-1} + \delta_3 lnT_{t-1} + \delta_4 lnE_{t-1} \\ &+ \sum_{j=1}^{k} \beta_{1j} \Delta lnCO2_{t-j} + \sum_{j=0}^{k} \beta_{2j} \Delta lnY_{t-j} + \sum_{j=0}^{k} \beta_{3j} \Delta lnT_{t-j} + \sum_{j=0}^{k} \beta_{4j} \Delta lnE_{t-j} \\ &+ \mu_{2t} \end{aligned} \tag{4}$$

$$\begin{aligned} ln\Delta T_t = \alpha_0 &+ \delta_1 lnCO2_{t-1} + \delta_2 lnY_{t-1} + \delta_3 lnT_{t-1} + \delta_4 lnE_{t-1} \\ &+ \sum_{j=1}^{k} \beta_{1j} \Delta lnCO2_{t-j} + \sum_{j=0}^{k} \beta_{2j} \Delta lnY_{t-j} + \sum_{j=0}^{k} \beta_{3j} \Delta lnT_{t-j} + \sum_{j=0}^{k} \beta_{4j} \Delta lnE_{t-j} \\ &+ \mu_{3t} \end{aligned} \tag{5}$$

$$\begin{aligned} ln\Delta E_t = \alpha_0 &+ \delta_1 lnCO2_{t-1} + \delta_2 lnY_{t-1} + \delta_3 lnT_{t-1} + \delta_4 lnE_{t-1} \\ &+ \sum_{j=1}^{k} \beta_{1j} \Delta lnCO2_{t-j} + \sum_{j=0}^{k} \beta_{2j} \Delta lnY_{t-j} + \sum_{j=0}^{k} \beta_{3j} \Delta lnT_{t-j} + \sum_{j=0}^{k} \beta_{4j} \Delta lnE_{t-j} \\ &+ \mu_{4t} \end{aligned}$$

(6)

In equations (3) to (6) the intercept term is α, first difference operator is Δ, parameter k is the lag order, and μ is the white noise error term assumed to be normally distributed and white noise.

From the equation above, the F-test is used to detect a long-run equilibrium relationship by testing the joint significance of the subset of coefficients of the lagged level variables. The null hypothesis of having no cointegration $H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$ is tested against the alternative hypothesis $H_1: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq 0$. The computed F-statistic is then compared with the first set of critical values called lower bound and with the second set of critical values called upper bound. They are computed by the surface response procedure for the F-test for cointegration in small samples (Turner, 2006). The null hypothesis of no cointegration is rejected if the calculated *F*-statistic exceeds the upper bound critical values. If it falls below the lower bound critical values, then the null hypothesis of no cointegration cannot be rejected. Other ways, the cointegration test is inconclusive if the calculated F-statistic lies between the two bounds. The constancy of the cointegration space is checked with the cumulative sum of recursive residuals and the cumulative sum of square of recursive residuals (Brown et al., 1975). Finally, the long and short-run coefficients of the model in question are estimated simultaneously.

Apart from testing the presence of cointegration, and representing short-run and long-run dynamics, this study also investigates short-run and long-run causal linkages, i.e. the direction of causality via the two-step Engle-Granger using a vector error correction model (Engle and Granger, 1987). According to the Granger representation theorem if there is cointegration then we should be able to find Granger causality in at least one direction. The first step of this method consists in deriving the error-correction terms from the long-run models of the variables of interest where these are expressed in level form. The second step consists in estimating the vector error correction models by including the error correction terms and all variables transformed in first differences as follows:

$$\Delta CO2_t = \alpha_1 + \sum_{i=1}^{p} \beta_i \Delta lnCO2_{t-i} + \sum_{i=1}^{p} \vartheta_i \Delta lnY_{t-i} + \sum_{i=1}^{p} \sigma_i \Delta lnT_{t-i} + \sum_{i=1}^{p} \theta_i \Delta lnE_{t-i} + \varphi_1 ECT_{t-1} + \tau_{1t} \tag{7}$$

$$\Delta Y_t = \alpha_2 + \sum_{i=1}^{p} \vartheta_i \Delta lnY_{t-i} \sum_{i=1}^{p} \beta_i \Delta lnCO2_{t-i} + \sum_{i=1}^{p} \sigma_i \Delta lnT_{t-i} + \sum_{i=1}^{p} \theta_i \Delta lnE_{t-i} + \varphi_2 ECT_{t-1} + \tau_{2t} \tag{8}$$

$$\Delta T_t = \alpha_3 + \sum_{i=1}^{p} \sigma_i \Delta lnT_{t-i} \sum_{i=1}^{p} \beta_i \Delta lnCO2_{t-i} + \sum_{i=1}^{p} \vartheta_i \Delta lnY_{t-i} + \sum_{i=1}^{p} \theta_i \Delta lnE_{t-i} + \varphi_3 ECT_{t-1} + \tau_{3t} \tag{9}$$

$$\Delta E_t = \alpha_4 + \sum_{i=1}^{p} \theta_i \Delta lnE_{t-i} \sum_{i=1}^{p} \beta_i \Delta lnCO2_{t-i} + \sum_{i=1}^{p} \vartheta_i \Delta lnY_{t-i} + \sum_{i=1}^{p} \sigma_i \Delta lnT_{t-i} + \varphi_4 ECT_{t-1} + \tau_{4t} \tag{10}$$

In equations (7) to (10) α *is* the intercept term and τ is the residual term. The difference operator is Δ and ECT_{t-1} is the one period lagged error-correction mechanism. Short-run

Granger causality can be exposed through a joint significance F-test on first differenced lagged explanatory variables. Long-run Granger causality is investigated through significance of the one period lagged error correction terms. On top of the Granger causality analysis, the strength of causal relations in the system will be assessed through the variance decomposition method. It assesses the breakdown of the forecast error variance to indicate which variables have short-term and long-term impacts on another variable of interest for the fifteen year time horizon.

3. Results and discussion

The results of the three unit root tests are reported in Table 1 and consistently suggest that the variables are integrated at the same order, but none of the variables is integrated higher than order one process. The data series follow a stationary process and are integrated at order one, being the order of integration one the number of differences needed to obtain a stationary process. Hence, the bounds testing approach to cointegration is applicable.

After the confirmation of the order of integration of the variables, we select the optimal lag length order of the unrestricted autoregressive distributed lag model with the Akaike information criterion. Since the calculation of the F-statistic for the cointegration test is sensitive to the number of lags in the dynamic model, the maximal lag to be used is set to one. The optimal lag structure is chosen by Akaike information criterion. Table 2 reports that there exist two cointegration relationships. The first one refers to the long-run equilibrium relationship between CO2 emissions, trade openness, real gross domestic product, and energy consumption. The second one refers to where real gross domestic product is the dependent variable. From the estimated results it can be concluded that the former is the preferred model specification since the *F*-statistic is 9.334 and greater than the critical values of the top level of the bounds. These results are statistically significant at the one, five and ten percent levels, and are valid for the case of no trend and unrestricted intercept, and for the unrestricted intercept and trend case. The estimated ARDL model has an overall satisfactory goodness of fit ($R^2 = 0.737$) and is statistically significant at conventional levels. The Durbin-Watson statistic is 2.017 indicating nearly no auto-correlation in the sample values. The diagnostic tests do not exhibit any evidence of violation of the classical linear regression model assumptions. Figure 1 shows that the cumulative sum of recursive residuals and squares residuals of the preferred CO2 emissions model has parameter constancy over the sample period since CUSUM and CUSUM of squares statistics are always within the five percent critical bounds of parameter stability.

We turn now to the measurement of the long-run parameters together with the short-run association among the variables. The former is estimated from the ARDL (1, 0, 1, 0) model and the latter is calculated considering an error correction model where the error correction term ECM_{t-1} is obtained from the cointegration equation. From the estimated results in Table 3 it is found that a 1 percent increase in energy consumption leads to an increase in 0.776 percent in CO2 emissions in the long-run. This result is statistically significant at the 10 percent level of significance whereas the parameters of the remaining variables are not. The short-run results indicate that energy consumption is statistically significant at the 10 percent level, but the size and magnitude of its effect is small. A 1 percent increase in energy consumption will only to an increase in 0.088 percent in emissions. The long-run elasticity of CO2 emissions with respect to energy consumption is greater than in the short-run. The strong correlation between energy consumption and emissions is not surprising. Trade openness is likely to have a negative effect on CO2 emissions in both short-term and long-term, but it is not statistically significant. Interestingly, economic growth is a positive and statistically significant driver of CO2 emissions in the short-run model. This finding is obtained at the 1 percent level of significance. The elasticity of emissions with respect to GDP is higher than unity meaning that a 1 percent increase in economic growth will lead to an increase in 1.123 percent in energy consumption. This means that over time higher energy consumption in Italy gives rise to more CO2 emissions and as a result the environment will be polluted more. With respect to economic growth, higher levels of economic development will lead to higher levels of CO2 emissions and this generally means more pollution in the short term. This is finding is of significant impact given the estimated size and magnitude of its parameter. The error correction mechanism has the correct negative sign and is statistically significant at the 1 percent level of significance. Its magnitude indicates a slow speed of adjustment towards long-run equilibrium in case of disequilibrium. These findings are robust since diagnostic tests do not signal misspecification for serial correlation, functional form, normality, and autoregressive conditional heteroscedasticity tests.

The Granger causality tests are reported in Table 4. They show evidence for a short-run and long-run bidirectional causal relationship between economic growth and energy consumption. The Granger long run causality results reveal statistical significance of the lagged error correction terms in the economic growth and in the energy consumption equations. Additionally there is a short-run unidirectional causal relationship running from trade openness to emissions and a short-run and long-run causal relationship running from trade openness to economic growth. There is also evidence of short-run and long-run unidirectional causality running from emissions to economic growth and energy consumption. There is no causal evidence running from economic growth to emissions which means that the Kuznets curve hypothesis is not validated.

Table 5 provides the decomposition of the variance to assess the relative strength of economic growth, trade openness and energy consumption in explaining the changes in CO2 emissions. The results report the percentage forecast variance explained by innovations tabulated for one to fifteen years time horizon using the Cholesky decomposition method. As expected own series shocks explain most of the error variance. It can be seen that, after fifteen years, a shock in economic growth explains only 2.832 percent of the forecast error variance of CO2 emissions, 2.662 percent of that of trade openness. A shock in CO2 emissions, however, accounts for about 46.658 percent of the forecast error variance of economic growth in the first year, 43.108 percent after three years, 30.472 percent after ten years, and 22.991 percent after fifteen years. This result is higher than for any other variable and supports the finding of short-run and long-run Granger unidirectional causality running from emissions to economic growth.

4. Conclusion

This study carries out an empirical investigation on causal relationships between CO2 emissions, economic growth, trade openness and energy consumption for a small open economy such as Italy. Moreover, it assesses the short-term and long-term drivers of CO2 emissions by applying unit root, cointegration, and Granger causality techniques to annual time-series data from 1960 to 2012.

Over the whole observation period, emissions, economic growth, trade openness and energy consumption are cointegrated. Moreover, energy consumption is a positive and statistically significant long-term and short-term driver of CO2 emissions. Energy consumption elasticity is high in the long-run and very low in the short-run. Thus, the strong correlation between energy consumption and pollutant emissions is not unexpected because CO2 emissions are usually calculated by multiplying the level of energy use by the average carbon content of fuels. An interesting finding is that economic growth is a positive and statistically significant strong driver of emissions in the short-run. Granger causality tests find support for the feedback hypothesis between energy consumption and economic growth in both the short-run and long-run. There is evidence for a short-run and long-run unidirectional causality relationship running from emissions to energy consumption and economic growth. Openness to trade Granger causes emissions in the short-run and economic growth in both the short-run and long-run.

Although the sample period has been extended, the findings obtained here are not conflicting with those of multi-country studies. However, from this analysis we infer that energy conservation policies may weaken economic growth of the Italian economy over time. To decouple energy consumption from economic growth, and in order to balance environment and economic development, low carbon alternatives, or renewable energy sources such as solar, hydro and wind power should be used instead of fossil fuels. Innovation and investment in research and development to design new energy saving technologies to curb pollutant emissions should be encouraged in the long-run.

Finally, this work is not without any limitations. Therefore, future research should try to model the known causal role that energy prices play in determining both the level of energy use and the mix of energy carriers, which affects average carbon content to deal with the issues of omitted variable bias. Future research should draw on trade theory to try to model how it affects environment and energy by introducing additional determinants and specifically addressing the role of financial development and foreign investments.

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Tables and Figures

Table 1
Results of unit root tests.

Variable	ADF	PP	DF-GLS
ln $CO2_t$	0.514 (3)	1.855 (5)	-0.758 (2)
	-3.125 (2)*	-3.417 (3)*	-3.315 (2)*
ln Y_t	-0.804 (0)	-0.712 (6)	-0.977 (6)
	-6.256 (1)*	-7.231 (6)*	-6.362 (0)*
ln T_t	-2.177 (0)	-2.148 (1)	-2.116 (0)
	-7.773 (0)*	-7.847 (3)*	-7.924 (0)*
ln E_t	-2.975 (2)	-2.049 (0)	-2.292 (2)
	-3.647 (2)^{a}	-6.840 (1)*	-3.637 (1)*

Note: The asterisks show statistical significance at the 1 percent level. The numbers in parentheses indicate the optimal lag order selection for ADF and DF-GLS tests, and bandwidth for the PP unit root test. The critical values for the ADF and PP tests are -3.562, -2.918 and -2.597, and -3.770, -3.190, -2.890 for the DF-GLS test at the 1, 5, and 10 percent levels of significance, respectively

Table 2
Results of cointegration tests.

Functional form	$CO2_t=f(Y_t,T_t,E_t)$	$Y_t=f(CO2_t,T_t,E_t)$	$T_t=f(CO2_t,Y_t,E_t)$	$E_t=f(CO2_t,Y_t,T_t)$
F-statisitc	9.334	5.591	2.204	3.393
R^2	0.737	0.618	0.185	0.317
Adjusted R^2	0.687	0.545	0.013	0.183
F-statistic	14.703*	8.500*	1.193	2.399
DW statistic	2.017	2.034	2.122	1.921
Diagnostic test	*F*-statistic (*p*-value)			
Serial correlation	0.051	0.155	2.884	0.007
	(0.821)	(0.693)	(0.092)	(0.930)
Functional form	0.001	1.269	1.792	0.212
	(0.967)	(0.260)	(0.181)	(0.645)
Normality	1.417	2.872	2.085	0.869
	(0.492)	(0.238)	(0.353)	(0.647)
Heteroscedasticity	0.308	0.449	1.028	0.424
	(0.579)	(0.503)	(0.311)	(0.515)

Level of significance	Critical values	
	Lower bounds *I*(0)	Upper bounds *I*(1)
1 percent	4.765 (5.748)	6.305 (7.293)
5 percent	3.419 (4.247)	4.673 (5.489)
10 percent	3.337 (3.585)	3.959 (7.704)

Note: The asterisks show statistical significance at the 1 percent level. The maximal lag length is set to 1. The optimal lag structure is determined by Akaike information criterion. The number in brackets is the order of diagnostic tests. Critical values bounds are computed by the surface response procedure proposed by Tuner (2006). They are reported for the case of no trend and unrestricted intercept. Figures in parenthesis are for the case of an unrestricted intercept and trend.

Table 3

Long-run and short-run analysis.

ARDL (1, 0, 1, 0)		
Dependent variable $\ln CO2_t$	Long-run parameter	t-statistic
Constant	0.837	0.391
$\ln Y_t$	0.132	-0.753
$\ln T_t$	-0.189	0.413
$\ln E_t$	0.776***	1.748
Dependent variable $\Delta \ln CO2_t$	Short-run parameter	t-statistic
Constant	0.095	0.403
$\Delta \ln Y_t$	1.123*	7.291
$\Delta \ln T_t$	-0.021	-0.781
$\Delta \ln E_t$	0.088***	1.848
ECT_{t-1}	-0.113*	-5.068
R^2	0.846	
Adjusted R^2	0.829	
F-statistic	63.469*	
DW statistic	2.010	
Diagnostic test	*F*-statistic	*p*-value
Serial correlation	0.153	0.695
Functional form	0.502	0.478
Normality	0.011	0.994
Heteroscedasticity	1.052	0.305

Note: The asterisks *, **, and *** indicate statistical significance at the 1, 5 and 10 percent level, respectively. The maximal lag to be used is 1. The optimal lag structure is chosen by Akaike information criterion.

Table 4

Results of Granger causality tests.

	Type of Granger causality				
Dependent variable	Short-run				Long-run
	$\Delta \ln CO2_t$	$\Delta \ln Y_t$	$\Delta \ln T_t$	$\Delta \ln E_t$	ECT_{t-1}
$\Delta \ln CO2_t$	-	0.114	11.061*	0.022	-0.041
		(0.736)	(0.001)	(0.881)	(-0.871)
$\Delta \ln Y_t$	5.385**	-	17.992*	3.781***	-0.119*
	(0.025)		(0.000)	(0.058)	(-3.005)
$\Delta \ln T_t$	0.021	0.001	-	0.093	-0.151
	(0.883)	(0.992)		(0.761)	(-1.388)
$\Delta \ln E_t$	3.639***	4.279**	0.001	-	-0.202**
	(0.062)	(0.044)	(0.985)		(-2.005)

Note: The asterisks *, **, and *** denote statistical significance at 1, 5 and 10 percent levels.
The F-statistic is reported for variables and coefficient on ECT. The values in parentheses are the *p*-value for variables and *t*-statistic for the ECT.

Table 5
Results of variance decomposition analysis.

Time horizon	S.E.	lnCO2$_t$	lnY$_t$	lnT$_t$	lnE$_t$
CO2 emissions					
1	0.011	100.00	0.000	0.000	0.000
3	0.018	82.293	0.073	15.073	2.560
5	0.022	64.256	1.150	21.199	13.393
10	0.028	39.373	2.451	36.799	21.275
15	0.033	30.529	2.832	50.202	16.431
Economic growth					
1	0.007	46.658	46.754	6.473	0.113
3	0.013	43.108	50.620	5.100	1.171
5	0.016	41.428	46.708	7.468	4.394
10	0.020	30.472	35.960	16.835	16.731
15	0.024	22.991	31.322	31.961	13.724
Trade openness					
1	0.028	15.959	0.000	83.722	0.318
3	0.042	9.488	0.154	88.328	2.028
5	0.049	7.022	1.226	85.106	6.644
10	0.054	5.815	2.563	78.991	12.629
15	0.055	5.823	2.662	78.657	12.856
Energy consumption					
1	0.014	0.009	0.000	0.000	99.991
3	0.022	6.505	4.729	0.171	88.594
5	0.024	8.160	4.342	5.631	81.866
10	0.029	6.581	10.587	28.353	54.477
15	0.031	6.919	12.960	31.972	48.148

Note: S.E. denotes the standard errors obtained over 1000 Monte Carlo replications. The Cholesky decomposition is the method of choice.

Figure 1

Plots of cumulative sum of recursive residuals and squares residuals for ARDL model