“Global CO₂ emissions, global energy consumption and global economic growth”

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SCHOOL OF SCIENCE & TECHNOLOGY
A thesis submitted for the degree of
Master of Science (MSc) in Energy Systems

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THESSALONIKI – GREECE
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ABSTRACT

This dissertation study was written as a part of the MSc in Energy Systems at the International Hellenic University and investigates the existence of causal relationship between economic growth, carbon dioxide emissions (CO₂ hereafter) and energy consumption for the sample period 1971-2011 within a global framework. In a first step, several unit root tests are implemented to detect the order of integration for each one of the time series, with or without breaks. All the variables are integrated of order one. In a second step, a number of tests are applied in order to discover the existence of cointegration in the series. The results reveal that no cointegration is evident. For the examination of causality, the well-known parametric causality tests of Granger, Toda-Yamamoto and Hsiao are used. According to the results, for the former there is causality running from energy consumption to CO₂ emissions with no feedback, while for the latter there is unidirectional causality once more running from energy consumption to CO₂ emissions but also from GDP to energy consumption as well as to CO₂ emissions. With regard to the last test, unidirectional causality is evident running from energy consumption to CO₂ emissions and from CO₂ emissions to GDP, whereas bi-directional causality exists between energy consumption and GDP. Eventually, two non-parametric causality tests are employed in order to identify possible non-linear causal relationships. At this point, I would like to express my sincere thanks to Professor E. Sartzetakis for supervising this study. Moreover, I would like to thank Dr. T. Dergiades who helped me with the E-Views software and supported me during the elaboration of this present dissertation.

Keywords: CO₂ emissions; economic growth; energy consumption; causal relationship.
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1. Introduction

Over the last few decades, it has become evident, at academic and political level, that climate change poses a serious threat to humanity. In response to this, a series of international conferences led to the development of the Kyoto protocol which was signed on 11 December 1997 in Kyoto, Japan. More specifically, it demands the emissions’ level to become 5.2% lower than the 1990 level during the period 2008-2012 for the developed countries. It came into force on 16 February 2005 while 191 states have signed and ratified the protocol. At the academic level, the research never stopped to enhance the understanding of the problem as well as to find new ways to battle for climate change. One of the crucial topics in the literature concerns the relationship between greenhouse-gas emissions, energy consumption and economic growth as measured by Gross Domestic Product (GDP).

The majority of the studies for the past two decades has been intensively focused and confirmed the relationships between economic growth and CO₂ emissions, as well as economic growth and energy consumption. In general, authors conclude that since CO₂ emissions attribute to economic growth, a reduction in emissions may not be a desirable outcome, especially in developing countries. Furthermore, since CO₂ emissions are related to both energy consumption and production, the existence of any relationships in the results between CO₂ emissions and economic growth may lead to important implications for economic and environmental policies. It is presumed that economic growth causes environmental changes and not vice versa. But it is being asserted that the nature and direction of causality may vary from one country to the other (Coondoo and Dinda, 2002).

Concerning to this relationship between economic growth and energy consumption, there are four points of view in the literature: the first considers that economic growth causes energy consumption and consequently, the higher the growth of a country’s economy is, the higher the demand for energy becomes; the second view deliberates for that energy consumption is responsible for economic growth; the third states that there is a causal nexus in both directions between energy consumption and economic growth whereas the last one, in contrast to the three aforementioned, argues that there is no causality running among them and thus the so-called ‘neutrality hypothesis’ takes place. In this case, energy conservation policies should be appropriate to cope with the reduction of CO₂ emissions without affecting economic growth.
With no doubt, the results of mixed across different countries because they depend on factors such as the sources of energy that have been used, the energy consumption level, the development path as well as the development stage and of course, the policies applied in each country.

For this purpose, the dissertation aims at contributing to this literature by investigating econometrically, within a multivariate framework, the relationship between CO₂ emissions, energy consumption and economic growth globally. Starting with the investigation of whether the time series are stationary or not, the testing procedure involves a number of unit root tests. The unit root tests are those required to identify the integration order of the three variables involved in the analysis. Namely, the Augmented Dickey-Fuller test (1979), the Generalized Least Squares de-trending Dickey-Fuller test and the Phillips and Perron (1988) test are implemented in a first step. Another stationarity test is the Kwiatkowski-Phillips-Schmidt-Shin (1992) test where under the null hypothesis the series assumed to be stationary (the opposite from the previous one where the null hypothesis states that the series are non-stationary). Finally, the tests of Zivot and Andrews (1992) as well as Perron (1989), both for one break, are used to reveal the existence of any structural breaks or not. Additionally, a supplementary test proposed by Kapetanios et al. (2003) and employed by Zhou et al. (2008) is used. It is a non-linear unit root test and presents a new technique regarding the null hypothesis of a unit root against an alternative one of the non-linear stationary smooth transition.

Subsequently, the tests for cointegration take place. Since the basic idea behind cointegration is to test whether a linear combination of two independently non-stationary time series is stationary by itself, the Johansen and Juselius (1990) and the Engle and Granger (1987) cointegration tests are applied to examine the existence of this long-run relationship among the variables. What is more, the presence of cointegration implies the existence of causality in at least one direction. Apart from these tests, the ARDL bounds testing developed by Pesaran and Shin (1998) and Pesaran et al. (2001) approach to cointegration is implemented because it contains several advantages in comparison to other cointegration procedures. The ARDL bounds testing approach is complementary to the Johansen’s maximum likelihood test, and it can be estimated by OLS. Although the Johansen method has disadvantages concerning small sample sizes and the different lag length, the ARDL approach
does not. Furthermore, it can be applied regardless of the order of integration that the time series have.

Next, in an attempt to identify non-linear causality, the non-linear dependence test proposed by Brock et al. (1996) is implemented, the widely known as BDS test. Since the BDS test can be applied to the residuals derived from the de-linearization of the series, the validity of the i.i.d. (independent and identically distributed) assumption on these data is examined. The de-linearization of the series occurs within a multivariate framework.

Then, it is time to test for the existence of causality between the variables under examination through a number of causality tests. The first one is the Standard Granger (1969) causality test, which is valid when variables have no cointegrating relationship. It is used in order to investigate the existence of a linear causality running among the three underlying variables. The second is the Toda-Yamamoto (1995) procedure for the existence of long-run Granger causality which, in contrast with others, does not require pretesting for cointegration. Hence, it enables feedback effects through several lags. Last but not least, is the Hsiao causality method (1979); a two-step method that combines the Akaike’s Final Prediction Error (FPE) with the Granger’s causality test through a Vector Error Correction Model (VECM) approach, in order to determine the optimum number of own-lagged and cross-lagged terms as well as the causality direction of two or more variables. All these tests are similarly characterized as parametric causality tests.

To conclude, the implementation of non-parametric causality tests is defined. To the best of our knowledge, not only there must be interest and focus on linear causality between the variables under investigation, but assumptions need to include relationships where non-linearity is evident. For this purpose, there are three sequential steps for testing the Hiemstra and Jones (1994) and Diks and Panchenko (2006) procedures. In the first one, both the tests are implemented directly into the level of the time series, whereas in the second step, both tests are reapplied on the de-linearized series through a multivariate Vector Autoregressive (VAR) specification. This step is of great importance to make sure that any detected causality is non-linear in nature. Lastly, the third step is to use a GARCH-BEKK filter for our multivariate framework. The GARCH BEKK (1,1) model is used in order to specify the variance and covariance equations. It is used to test for the second moment filtering at GARCH residuals.
The dissertation is structured as follows: The second chapter will present a critical review of the literature. The third chapter will lay out the data and methodology that will be used, while the fourth chapter will present the empirical application. The fifth chapter will present and explain the results, while the sixth chapter will discuss policy recommendations. The last chapter will present the main conclusions and the limitations of the dissertation and discuss the most important extensions that can arise from these research findings.

2. Literature Review

In the literature, it is apparent that a significant number of studies examined the causal nexus between environmental pollutants, energy consumption, and economic growth. As a result, there are different empirical findings with regard to the direction of causalities between the variables. There are countries where bi-directional causality is evident while others that suggest the neutrality hypothesis. For some countries, unidirectional causality exists running from one variable to another with no feedback and vice versa. In this dissertation, the investigated studies are separated in those investigations that took place in developed countries, in developing countries or, lastly, in Group of countries either developed, or developing, or mixed.

To begin, Soytas et al. (2007) analyze the case of the United States during the time period of 1960-2004 with regard to the linkages that exist between the variables of CO₂ emissions, energy consumption and GDP, including gross fixed capital and labor in the model. The actual attempt in this study is to consider the theory behind the growth-emissions nexus, by evaluating the relationship between CO₂ emissions and real output, while accounting for the three variables of energy consumption, labor and fixed capital. Applying the Toda-Yamamoto (1995) procedure the results indicate that, in the long-run, GDP does not Granger cause CO₂ emissions but energy consumption does with no feedback and apparently, the main cause of CO₂ emissions and energy consumption. Additionally, some innovation accounting methods are employed to provide the results. Apparently, economic growth may not be the solution for emission reduction and the environmental problems in US. Similarly, a research took place in another developed country, Canada, by Ghali (2004) who attempts to examine the causality between energy consumption and output growth for the sample period of 1961-1997. In the study, a neo-classical, one-sector aggregate production technology is used where energy,
capital and labor are treated as separate units. The Johansen (1990) cointegration technique is applied in order to reveal the long-run relationship of the variables. Then, the Vector Error Correction Model (VECM) is used for testing the short-run. The results indicate that bidirectional causality holds between output growth and energy consumption. Consequently, energy is a limiting factor to output growth since it causes a negative effect, while can be considered as an important policy implication for Canada.

Narayan and Smyth (2005) examine the causal nexus between electricity consumption, employment and real economic growth for the case of Australia during the time period of 1966-1999. An Unrestricted Error-Correction Model (UECM) is utilized to explore the existence of long-run relationship. The results reveal that all the three variables are cointegrated. Additionally, unidirectional causality runs from economic growth to electricity consumption in the long-run, while in the short-run a weak unidirectional causality running from economic growth to electricity consumption exists. What is evident from the conclusions is that Australia can undoubtedly implement electricity conservation policies via efficiency measures and demand policies that do not have a negative impact on the country’s real economic growth. Another island country in the Pacific, New Zealand, and the causal nexus between energy consumption and economic growth were investigated by Bartleet and Gounder (2010). The results were both for the long-run and the short-run for the sample period of 1960-2004. Something to be mentioned is the use of trivariate demand-side and multivariate production models for the investigation of the causal linkages between energy and macroeconomic variables. Concerning the demand model, the estimated findings indicate a long-run relationship between energy consumption, real GDP and energy prices. In the short run, Granger’s causality exists from real GDP to energy consumption with no feedback effect. There is the indication that energy prices seem to be significant for energy consumption outcomes. With regard to the production model, a long-run relationship among energy consumption, economic growth and employment is evident. The presence of Granger’s causality from real GDP to energy consumption provides additional evidence that energy consumption in New Zealand is connected to the economic growth and activities.

One of the two pillars of European Union’s economy, France, was explored by Ang (2007). He explored the dynamic causality between energy consumption, pollutant emissions and output for the covering period of 1960-2000. The applying techniques for the analysis are unit root tests, the Johansen’s approach, the autoregressive distributed lag (ARDL) bounds
test by Pesaran et al. (2001) and last but not least the Error Correction Model (ECM) based causality test. The empirical results of the study provide evidence for the existence of a strong long-run relationship between the variables. This happens due to the fact that economic growth affects the growth of energy consumption as well as the growth of pollution. More precisely, the more energy consumption results in more CO₂ emissions, and CO₂ emissions and output have a quadratic relationship in the long run. Additionally, the results conclude to a unidirectional causality running from energy consumption to economic growth in the short-run. On the other hand, Tsani (2009) investigates the case of Greece, the country in the deepest crisis nowadays, and the causal relationship between energy consumption and economic growth for the sample period of 1960-2006. The variable of energy consumption is separated in aggregated and disaggregated levels in order to assess the existence of any causal nexus. For the data analysis, unit root tests are applied, and thereafter, the Toda-Yamamoto approach is used to eliminate the need for cointegration testing. According to the results, at aggregated levels of energy consumption appears a unidirectional relationship running from energy consumption to real GDP. However, at disaggregated levels, the existence of a bi-directional causality is evident concerning the industrial and the residential energy consumption. As far as the transport energy consumption is concerned, is not included since, neutrality exists. In general, the findings of the study indicate that in the case of Greece emphasis should be put on the demand and energy-efficiency improvements via energy conservation policies in order not to deter economic growth as well as to address energy import dependence. Another country heavily affected by the economic crisis in Europe, Portugal, was examined by Shahbaz et al. (2011) in an attempt to discover the causal relationship between economic growth, electricity consumption and employment during the period from 1971 to 2009. Unit root tests and the bounds’ testing approach is used to discover whether co-integration and a long-run equilibrium relationship exist within the application of UECM. Then, in order to find the direction of Granger’s causality between the variables, the VECM is applied. The documented evidence from the results indicates that, in the long-run, the three variables are cointegrated and move together since a bi-directional causality holds between energy consumption, economic growth and employment. In the short-run, except for the causality among electricity consumption and economic growth, the remaining variables have a Granger’s causality running in both directions. What is more, a unidirectional causality is evident running from economic growth to electricity consumption with no feedback effect in the short-run. Consequently, there is a conflict for the appropriate policies that must be
adapted in the long- and the short-run. To this end, in the short-run energy conservation policies must be applied while in the long-run environmentally friendly or renewable-energy policies must be utilized in order not to affect economic growth.

Wankeun and Lee (2004) study the causal relationship between economic growth and energy consumption in Korea over the time period of 1970-1999 by applying a multivariate model of energy, GDP, capital and labor. The log mean Divisia index method was used in order to mitigate aggregation bias. Since there was strong evidence that the variables were cointegrated, the VECM was preferred rather than a VAR to test for Granger’s causality as well as the short-run relationship and the long-run dynamics. What the empirical results reveal is the existence of a long-run bi-directional causality between energy consumption and GDP, and a short run unidirectional causal relationship running from energy consumption to GDP.

On the other side, there are the papers that are related to some of the world’s developing countries. A significant number of papers is related to studies that took place in China, direct or indirectly. There are not few studies that draw a lot of interest on the case of China for the specific causality topic. Zhang and Xin (2011) analyze the statistical data from 1980 to 2008 of Shandong Province in China. For the analysis unit root, cointegration and Granger’s causality tests applied in order to examine the relationship between economic growth and energy consumption. The variables included are energy consumption, GDP, fixed asset investment and employees. The results reveal that there is long-term relation as well as Granger’s causality runs in both directions between energy consumption and economic growth. The Generalized Least Square (GLS) method is used to estimate the econometric model. Model estimation results further confirm that energy consumption plays a greater role in economic growth. The conclusions that come up to the positive correlation in addition to the high dependence between energy consumption, and economic growth gives reasons to relevant policy recommendations such as the industrial structure’s upgrading, the further increase investment in science and technology and other measures to stimulate enterprises and individuals to participate in energy conservation.

Chandran and Sharma (2010) explore the causal relationship between electricity consumption and real GDP in Malaysia for the sample period of 1971-2003. This particular study applies a bivariate as well as a multivariate (when the price variable is added)
framework. The time-series data are examined by using unit root tests in a first step. The ARDL bounds testing approach of cointegration is employed afterwards in order to possibly identify for a long-run relationship between the variables. The results obtained indicate that a long-run relationship does exist between electricity consumption, real GDP and price. What is more, there is evidence that in the short-run, unidirectional causality with no feedback effects running from electricity consumption to economic growth exists. Thus, Malaysia is apparently an energy-dependent country, and some policy implications should be drawn. The analysis for the case of Taiwan and the causal nexus between energy consumption and economic growth occurred by Cheng and Lai (1997) for the period during 1955-1993. The available data are analyzed, firstly, by using a unit root test to ascertain stationarity while the Hsiao’s version of the Granger’s causality method follows. The estimated results indicate that causality runs from GDP to energy consumption with no feedback. Furthermore, it is found that causality exists running from GDP to energy but not vice versa. Wolde-Rufael (2004) examines the causal relationship between various kinds of industrial energy consumption and GDP during 1952-1999 in Shanghai. The available data are analyzed by using the Toda-Yamamoto (1995) causality test. What the empirical results indicate is a unidirectional Granger’s causality that runs from coal, coke, electricity and total energy consumption to real GDP while no causal relationship in either direction is evident between oil consumption and real GDP. Hence, judging from the findings, a reduction in energy consumption may lead to a fall in economic growth so the appropriate measures and policies should be employed.

Important studies also took place for the country of India. Again, Wolde-Rufael (2010) makes attempts to test if causal relationship exists between economic growth and nuclear energy consumption for India for the period 1969-2006. Using the bounds testing approach to cointegration the indication of a short-run and a long-run relationship between energy consumption and economic growth revealed. Further, the application of the Toda and Yamamoto (1995) approach to Granger’s causality and the variance decomposition approach developed by Pesaran and Shin (1998), gave a positive and a significant unidirectional causality running from nuclear energy consumption to economic growth without feedback. The implication following the above results shows that economic growth in India depends on nuclear energy consumption where a decrease in nuclear energy consumption may lead to decrease in real economic growth. In the same way, Paula and Bhattacharya (2004) examine the causal relationship between energy consumption and economic growth in India covering
the sample period of 1950-1996. Using the Standard Granger’s causality and the Engle-Granger (1987) Error Correction Model approach when energy is considered as a dependent variable, some combined results come up with the indication that bi-directional causal relationship exists between energy consumption and economic growth. The results that obtained by each one of the approaches are as follows: the Standard Granger’s causality test implies a unidirectional causal relation from energy consumption to GDP while the Engle-Granger cointegration process exhibits a unidirectional long-run causality running from GDP along with capital to energy consumption. The application of the Johansen multivariate cointegration approach on the different set of variables afterwards, reveals the existence of long-run causality running from economic growth to energy consumption and the short-run causality runs from energy consumption to economic growth.

A country that is located in the continent of Africa, Tanzania, has been examined by Odhiambo (2009) in order to detect the causal relationship between energy consumption and economic growth during 1971-2006. The available data was examined by the ARDL bounds testing approach to reveal this existing relationship. Something worth-mentioned is the usage of two proxies of energy consumption, more specifically total energy consumption per capita and electricity consumption per capita against a proxy for economic growth namely real GDP per capita. The bounds testing approach of the study results in a long-run relationship between each one of the proxies. On the other hand, the findings of the causality test indicate the existence of unidirectional causality running from total energy consumption, as well as electricity consumption, to economic growth. Evidently, the general conclusions end up to the fact that energy consumption spurs economic growth.

In a last step, the studies examined are referred to group of countries. For instance, and to be more precise, Ozturk and Acaravci (2010) investigate four East-European countries in an attempt to investigate the causal relationship between energy consumption and economic growth. The examined period is extended from 1980 to 2006 while the Engle and Granger (1987) model is applied in two steps to indicate the results. Firstly, in order to find the long-run relationship between the variables, the (ARDL) bounds test approach of cointegration is employed. Next, the direction of causality is uncovered by the usage of the VECM. The estimated findings reveal that there is no cointegration between the variables for Albania, Bulgaria and Romania and so, any causal relationships within the dynamic ECM cannot be estimated. On the other hand, for the remaining one, Hungary, a Granger’s causality that runs
in both directions is evident between energy consumption per capita and real GDP. Consequently, the implementation of any policy in these countries should be based on their economic situation. Staying in the European continent, Žiković and Vlahinić-Dizdarević (2011) study the case of twenty-two small European countries and the causal nexus between the oil consumption and the economic growth covering the period of 1980-2007 for the developed countries, and 1993-2007 for the countries in transition. Unit root tests and the ECM employed to provide the desired results. The estimated findings indicate the division of the twenty-two European countries in two groups. The first group is characterized by the causality running from real economic growth to oil consumption in the most developed countries and in the transition countries while the second by the causality from oil consumption to economic growth.

Some studies include either a number of developed countries, or a number of developing countries. For example, Lee et al. (2008) study a panel of 22 OECD countries over the period of 1960-2001. The examined variables are three: energy consumption, economic growth and capital stock. The investigation becomes by using an aggregate production function, controlling, and last but not least exploring the directions of the causality between the three variables. In a first step, it becomes evident that a strong long-run equilibrium relationship exists among the variables. Secondly, there are indications that stock capital is much more productive than energy consumption. Thirdly, it is observed that whether the impact that capital stock has on economic growth is neglected, the effect of energy consumption on economic growth is overestimated. Last but not least, the panel causality test indicates a causality running in both directions between energy consumption, economic growth and capital stock. In the conclusions, it is obvious that capital stock plays a significant role in the relationship among energy and economic growth. In the same line, Lee (2006) explores the relationship between energy consumption and economic growth in eleven major industrialized countries or else, the G-11 countries during the period 1960-2001, except for Germany where data are available for 1971-2001 and Canada for 1965-2001. The Toda-Yamamoto (1995) procedure is applied in order to test Granger’s causality among the variables. In accordance with the results, in Germany, United Kingdom and Sweden there is no causality between energy consumption and GDP is observed with respect to each other, whereas the United States is the only one where causality is running in both directions. Further, unidirectional causality runs from energy consumption to economic growth for Belgium, Canada,
Netherlands and Switzerland while in France, Italy and Japan, a unidirectional but reversed causal relationship has been found. In other words, for the first group of four countries it is evident that the implementation of any energy conservation policy may harm economic growth. For the three remaining countries, energy conservation policies could have very few or even no effects on economic growth and thus, these are the most appropriate countries for the development of such policies. There is evidence that if the same causality test method is employed, the results differ.

Soytas and Sari (2003) study and reexamine the causal relationship between energy consumption and GDP in the top ten emerging markets, excluding China due to lack of data, and G-7 countries. The VECM is applied to test for the causality that exists between the variables for the time period of 1950-1992. To this end, the results indicate bi-directional causality in the case of Argentina. On the other hand, unidirectional causality with no feedback runs from GDP to energy consumption in Italy and Korea, and from energy consumption to GDP in Turkey, France, Germany and Japan. Consequently, it is evident for these countries that the adoption of energy conservation policies may harm economic growth instead of improve it. Over again, the G-7 countries and the relationship between energy consumption and GDP were investigated by Soytas and Sari (2006). The period of data covered differs since some French data are during 1971-2002; some German data are during 1971-2003 while for most of the variables the sample period is during 1960-2004. For the analysis of the data, multivariate cointegration models are employed in the beginning and ECM as well as generalized variance decompositions follow in order to reveal the causal relationship between the variables for all the countries. The results reveal that long-run causality exists in all G-7 countries. More specifically, in four of the countries -Canada, Italy, Japan and UK- bi-directional causality seems to be uncovered, in two of them -US and France- unidirectional causality runs from energy consumption to economic growth while only in Germany the causality runs from GDP to energy consumption with no feedback. Since the causal direction is different among the countries, different policies should be available in each country. In accordance with the results, the implementations of energy conservation measures are suggested to be effective for a fight against global warming in Germany, whereas, in France and US technological developments and mitigation policies could have a positive impact. In Canada, Italy, Japan and UK, a combination of alternative policies could be the appropriate choice.
Keeping the interest at the side of the American continent, Yoo and Kwak (2010) attempted to examine the causality between economic growth and electricity consumption for seven South American countries. The sample period that covered is from 1975 to 2006 while time-series techniques are adapted to analyze the data. More specifically, unit root and cointegration tests are applied before the application of Granger’s causality tests. In order to test for the direction of Granger’s causality a number of models were estimated as well. It is obvious from the findings that the causal nexus between the two examined variables varies across countries. Apart from this though, there is short-run, unidirectional causal relationship running from electricity consumption to GDP for Argentina, Chile, Columbia and Ecuador and bi-directional causality between the variables in Venezuela. No causal relationship exists in Peru. Apparently, based on the first case, there is the indication that an increase in electricity consumption indirectly affects economic growth in the group of countries with the unidirectional causality. On the other hand, the bi-directional relationship in Venezuela reveals that a rise in electricity consumption directly affects economic growth while economic growth in turn also stimulates further electricity consumption in the country.

Some studies give their greatest interest at the oil-exporting countries such as particular studies of Mehrara (2007). He examines the causal relationship between energy consumption per capita and GDP per capita in a panel of 11 oil-exporting countries. The covering period is for 1971-2002. In the analysis, panel unit root tests as well as panel cointegration techniques are employed to investigate whether there is causality between the two economic series. Applying Granger’s causality test, the results reveal the existence of a strong unidirectional causality running from GDP to energy consumption with no feedback. This indicates that the GDP drives the energy consumption rather than the energy consumption. Consequently, a feasible policy for economic growth would be the energy conservation for this specific group of countries. Again, Mehrara (2007) investigated the causal nexus between energy consumption and economic growth for three oil-exporting countries: Iran, Kuwait and Saudi Arabia. The analysis begins with the usage of unit root tests while continues with two different methods to test for causality, more specifically, the ECM and Toda-Yamamoto (1995) approach. With regard to the first model, the results show a unidirectional causality with no feedback effects running from economic growth to energy consumption for Iran and Kuwait is evident in the long-run. Contrariwise, in the short-run neutrality is observed between the two variables. For the case of Saudi Arabia, a strong unidirectional causality
appears from energy consumption to economic growth. Concerning the Toda-Yamamoto (1995) approach the same results are revealed: unidirectional causality runs from GDP to energy consumption for Iran and Kuwait whereas for Saudi Arabia energy consumption, Granger causes economic growth. Something apparent for both methodologies is that in case of Saudi Arabia, causality is highly significant at all levels, while for Iran and Kuwait seems to be rather significant. Hence, according to the results, different policies are recommended in each country: conservation policies for Iran and Kuwait since they cannot have a negative impact on economic growth and measures that do not affect economic growth from Saudi Arabia.

Leaving the groups of oil-rich countries, Wolde-Rufael (2006) examines the long-run and causal relationship between real GDP per capita and electricity consumption per capita for 17 African countries during the period of 1971-2001. The combination of the cointegration test proposed by Pesaran et al. (2001), as well as the Toda-Yamamoto (1995) approach, is used in order to avoid the pre-testing with unit root and cointegration tests. The empirical results that obtained reveal that a long-run relationship exists between electricity consumption per capita and real GDP per capita for 9 of the countries while Granger’s causality exists for 12 of the countries. Concerning the causality between the variables examined, the results indicate that a positive unidirectional causality runs from real GDP per capita to electricity consumption per capita for six countries; an inverse causality exists for three countries, and a bi-directional causality exists for the remaining three countries. Something to be mentioned is that electricity consumption in Africa accounts for less than 4% of total energy consumption and only grid-supplied electricity is taken into account for the study. What is more, the directions of causality are not defined exactly between the variables since there are a number of factors that significantly differ across each one of the countries. Odhiambo (2010) examines the case of three sub-Saharan African countries, more specifically, South Africa, Kenya and Congo (DRC) and the causal relationship that exists between the variables of energy consumption and economic growth in these countries. The time period covered is from 1972 to 2006. The ARDL bounds testing procedure is employed to find the causality between the variables which varies significantly across the countries. The estimated results indicate a unidirectional causality running from energy consumption to economic growth for South Africa and Kenya, whereas, for the case of Congo (DRC), a reversed unidirectional causality from economic growth to energy consumption is evident. According to the findings above, different policies
have to be implemented in these two different cases. More specifically, in the case of Congo energy conservation should be the appropriate choice since they do not significantly affect economic growth. On the other hand, in the case of South Africa and Kenya, the long-run energy demand should be preserved by a further increase on energy supply while in the short run the energy dependency problem should be coped with more efficient and cost-effective sources of energy.

The Association of South East Asian Nations (known as ASEAN countries) which includes four members, Indonesia, Malaysia, Singapore and Thailand were investigated by Yoo (2006). According to the data availability, the examined period is during 1970-2002 while causality tests for detecting any relationship between electricity consumption, and economic growth have been performed by using time series techniques. More specifically, unit root and cointegration tests have been applied before Granger’s causality test and thereafter, several models were estimated in order to test for the direction of Granger’s causality. To this end, the results that came up indicate that a bi-directional causality exists between the two variables in Malaysia and Singapore, whereas in Indonesia and Thailand, unidirectional causality runs from economic growth to electricity consumption with no feedback effect. Hence, the first results indicate that an increase in electricity consumption directly affects economic growth as well as economic growth further stimulates electricity in both countries. On the other hand, the results concerning the two remaining countries’ conservation policies can be performed with no effects on economic growth. However, with regard to all the four countries significant causal relationship between electricity consumption and economic growth becomes evident.

Asafu-Adjaye (2000) examines the causal relationship between energy consumption and economic growth for a number of Asian developing countries. The variable of price is included in the study as a third variable. The sample period covered is between 1973-1995 for Thailand and the Philippines and between 1971-1995 for India and Indonesia. The analysis of the time-series data results from the maximum likelihood procedures while ECM was estimated to discover whether there is Granger causality. In accordance with the findings of the study, unidirectional causality running from energy consumption to GDP is apparent for India and Indonesia, whereas bi-directional causality holds for Thailand and the Philippines both in the short-run. In the long-run, causality running from energy consumption and prices to economic growth is detected for India and Indonesia. The causality case of South Korea
and Singapore for the causality issue between energy consumption and GDP was investigated by Glasure and Lee (1997). The sample period is extended between 1961 and 1990. First of all, in the study, the Akaike’s Information Criterion (AIC) is used in order to define the optimal lag length for the system. Based on the results concerning the stationarity of the variables, the cointegration and causality tests follow. In the analysis, the ECM and the standard Granger’s causality test are used. The conclusions illustrate that bi-directional causality exists between energy consumption and GDP for both South Korea and Singapore with regard to the error correction models. In the same way, applying the standard Granger’s causality tests results in no causal relationship between energy consumption and GDP for South Korea, but reveals unidirectional causality from energy consumption to GDP for Singapore.

Up to now, the basic literature has been presented regarding the causal relationships between the variables of CO2 emissions, energy consumption and economic growth. Table 1 that follows summarizes all the studies discussed as a whole.

<table>
<thead>
<tr>
<th>Source</th>
<th>Country</th>
<th>Period</th>
<th>Methodological Framework</th>
<th>Causality inference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tsani (2010)</td>
<td>Greece</td>
<td>1960-2006</td>
<td>TY causality test</td>
<td>EC→GDP (aggregated levels) EC(industrial &amp; residential) GDP(disaggregated levels)</td>
</tr>
<tr>
<td></td>
<td>Authors</td>
<td>Country</td>
<td>Period</td>
<td>Method</td>
</tr>
<tr>
<td>---</td>
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<td>------------------------</td>
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<td>-------------------------</td>
</tr>
<tr>
<td>9</td>
<td>Soytas and Sari (2009)</td>
<td>Turkey</td>
<td>1960-2000</td>
<td>TY causality Test</td>
</tr>
<tr>
<td>10</td>
<td>Halicioglu (2009)</td>
<td>Turkey</td>
<td>1960-2005</td>
<td>ARDL, ECM causality</td>
</tr>
</tbody>
</table>

**Panel B: Developing Countries**

<table>
<thead>
<tr>
<th></th>
<th>Authors</th>
<th>Country</th>
<th>Period</th>
<th>Method</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>Alam <em>et al.</em> (2010)</td>
<td>Bangladesh</td>
<td>1972-2006</td>
<td>JJ, VECM causality ARDL, ECM causality</td>
<td>EC≠GDP (short run) GDP→EC (short and long run) CO₂→GDP (short and long run) EC→CO₂ (short and long run)</td>
</tr>
<tr>
<td>19</td>
<td>Lotfalipour <em>et al.</em> (2010)</td>
<td>Iran</td>
<td>1976-2007</td>
<td>TY causality test</td>
<td>GDP→EC (petroleum products and natural gas consumption) EC≠CO₂ (total fossil fuels consumption)</td>
</tr>
<tr>
<td></td>
<td>Author(s)</td>
<td>Country</td>
<td>Period</td>
<td>Methodology</td>
<td>Direction of causality</td>
</tr>
<tr>
<td>---</td>
<td>-----------------------------------------------</td>
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</tr>
</tbody>
</table>

**Panel C: Group of countries either developed, or developing or mixed**

<table>
<thead>
<tr>
<th></th>
<th>Author(s)</th>
<th>Number of countries</th>
<th>Period</th>
<th>Methodology</th>
<th>Direction of causality</th>
</tr>
</thead>
<tbody>
<tr>
<td>30.</td>
<td>Žikoviæ and Dizdareviæ (2011)</td>
<td>22 Small European countries</td>
<td>1980-2007</td>
<td>JJ, VECM causality S. Granger test TY causality test</td>
<td>GDP→ Oil consumption (Developed countries: Scandinavian economies, Ireland and Belgium), (Transition countries: Croatia, Latvia, Lithuania and Moldova), Oil consumption → GDP (Austria, Czech Republic, Slovakia, Malta, Bulgaria and Bosnia and Herzegovina)</td>
</tr>
<tr>
<td></td>
<td>Authors (Year)</td>
<td>Sample</td>
<td>Period</td>
<td>Methodology</td>
<td>Results</td>
</tr>
<tr>
<td>---</td>
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<td>---------</td>
</tr>
<tr>
<td>32.</td>
<td>Lee (2006)</td>
<td>G-11 countries</td>
<td>1960-2001, 1971-2001 (Germany), 1965-2001 (Canada)</td>
<td>TY causality test</td>
<td>EC ↔ GDP (UK, Germany and Sweden), EC ↔ GDP (US), EC → GDP (Canada, Belgium, the Netherlands and Switzerland), GDP → EC (France, Italy and Japan)</td>
</tr>
<tr>
<td>33.</td>
<td>Soytas and Sari (2003)</td>
<td>G-7 countries: Argentina, France, Germany, Italy, Japan, Korea, Turkey</td>
<td>1950-1992</td>
<td>JJ, VECM causality</td>
<td>GDP ↔ EC (Argentina), GDP → EC (Italy and Korea), EC → GDP (Turkey, France, Germany and Japan)</td>
</tr>
<tr>
<td>36.</td>
<td>Chang and Soruco Carballo (2011)</td>
<td>Latin America and the Caribbean</td>
<td>1971-2005</td>
<td>JJ, VECM causality</td>
<td>EC → GDP (Uruguay, Peru), CO₂ → EC (Bolivia), EC → GDP, CO₂ (Brazil, Ecuador, Jamaica, Nicaragua, Peru, Trinidad and Tobago and Uruguay), GDP → CO₂, EC (Argentina, Brazil, Chile, Columbia, and Ecuador)</td>
</tr>
<tr>
<td>37.</td>
<td>Yoo and Kwak (2010)</td>
<td>7 South-American countries: Argentina, Brazil, Chile, Columbia, Ecuador, Peru, and Venezuela</td>
<td>1975-2006</td>
<td>JJ, VECM causality, EG, VECM causality, S. Granger causality test, Hsiao causality method</td>
<td>EC → GDP (Argentina, Brazil, Chile, Columbia, and Ecuador), EC → GDP (Venezuela), EC ↔ GDP (Peru)</td>
</tr>
<tr>
<td>No.</td>
<td>Author(s)</td>
<td>Region/Type</td>
<td>Period</td>
<td>Methodology</td>
<td>Findings</td>
</tr>
<tr>
<td>-----</td>
<td>--------------------</td>
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<td>-----------------------------------------------</td>
</tr>
<tr>
<td>44.</td>
<td>Pao and Tsai (2010)</td>
<td>BRIC countries: Brazil, Russia, India and China</td>
<td>1971-2005 (Except for Russia 1990-2005)</td>
<td>EG, VECM causality TY causality test</td>
<td>CO₂ ↔ EC EC ↔ GDP (long run) EC → GDP (short run) CO₂ → GDP</td>
</tr>
<tr>
<td>47.</td>
<td>Sari and Soytas (2007)</td>
<td>Indonesia, Iran, Malaysia, Pakistan, Singapore, and Tunisia</td>
<td>1971-2002, 1974-2002 (Iran)</td>
<td>VAR systems</td>
<td>The direction of causality is not mentioned</td>
</tr>
<tr>
<td>48.</td>
<td>Glasure and Lee (1997)</td>
<td>South Korea and Singapore</td>
<td>1961-1990</td>
<td>EG, VECM causality S. Granger causality test</td>
<td>EC↔GDP GDP≠EC (South Korea) EC→GDP (Singapore)</td>
</tr>
</tbody>
</table>

Notes: EC and GDP denote energy consumption and Gross Domestic Product, respectively. → indicates unidirectional causality, whereas ↔ and ≠, respectively, imply bi-directional causality and absence of causality. JJ stands for Johansen and Juselius’s (1990) cointegration approach; EG stands for Engle and Granger (1987) approach to cointegration; TY implies the Toda-Yamamoto (1995) causality test and eventually, ARDL represents the bounds testing approach by Pesaran and Shin (1998) and Pesaran et al. (2001).

### 3. Data and Methodological Framework

#### 3.1 Data

This study employs annual data in a worldwide level for CO₂ emissions (CO₂), energy consumption (EC) and gross domestic product (GDP) from the World Development Indicators (WDI) database from the World Bank. Due to data availability, the sample period examined is from 1971 to 2011. The CO₂ emissions are measured in kilotons of CO₂, the energy consumption in kilotons of oil equivalent and GDP in millions of US dollars at constant 2000 prices. All the variables used are expressed in natural logarithms. The following figures depict the three key variables of the study into levels and in growth rates.

**Figure 1. World CO₂ (Logarithms)**

**Figure 2. World CO₂ (Growth Rates)**
3.2 Unit root tests

The unit root tests are those required so as obtaining the maximal integration order of the three variables involved in the analysis. More specifically the time series are characterized as integrated of order zero, one or two (orders that are beyond the number of two are really scarce). For instance, if the series contain a unit root in its levels, but they are stationary at their first differences, this indicates that they are integrated at order one i.e., I(1). There is a null hypothesis tested, which suggests that the variable under investigation contains a unit root (or else the time series are non-stationary) against an alternative that does not (or else the time series are stationary). In each one of the cases, the optimal lag-length is chosen with the usage of the Akaike Information Criterion (AIC). These tests are presented in detail next, and
namely, they are the Augmented Dickey-Fuller test (ADF), the Generalized Least Squares detrending Dickey-Fuller (GLS-DF) test and the Phillips and Perron test (PP).

3.2.1 Augmented Dickey-Fuller test

The standard ADF test is estimated by the following equation:

$$
\Delta y_t = a y_{t-1} + x_t' \delta + \epsilon_t,
$$

where $\alpha = \rho - 1$. Consequently, the null and alternative hypotheses can be written as,

$$
H_0 : \alpha = 1
$$
$$
H_1 : \alpha < 1
$$

and is evaluated by using the conventional $t$-ratio for $\alpha$:

$$
t_{\alpha} = \hat{\alpha} / (se(\hat{\alpha}))
$$

where $\hat{\alpha}$ is the estimate of $\alpha$, and $se(\hat{\alpha})$ is the coefficient standard error.

Dickey and Fuller (1979) demonstrate that under the null hypothesis, a unit root statistic does not follow the conventional Student's $t$-distribution. For the various tests and the different sample sizes, they derive asymptotic results as well as simulate critical values. This particular Dickey-Fuller unit root test is valid only in the case the time-series is an AR(1) process. The assumption of white noise disturbances $\epsilon_t$ is violated whether the series are correlated at higher order lags. Thus, for higher-order correlation, the ADF test is the one that makes a parametric correction. This is obtained as follows:

$$
\Delta y_t = a y_{t-1} + x_t' \delta + \beta_1 y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p} + \nu_t
$$

where $y$ is the time series (follow AR($p$) process) and $p$ the lagged difference terms. This specification is used to test (2) using the $t$-ratio (3).

To conclude, concerning the performance of the ADF test, two practical issues are evident in the analysis. Firstly, the choice of whether exogenous variables will be included in the test regression or not. There are three options to choose for inclusion in the test regression which are a constant, a constant and a linear time trend or lastly, neither of them. The most
appropriate one to run the regression is considered to be the second with both a constant and a linear trend since the other two seem to be more special cases. However, something to be mentioned is the reduction of the test power to reject the null hypothesis of a unit root in the case that we include irrelevant regressors.

Second, the optimal “lag length” has to be specified in order to be added in the regression. The “lag length” is the term that we use to specify the number of lagged difference terms in the test regression. The standard ADF test yields zero, whereas integers greater than zero correspond to the ADF tests. The problem of choosing the number of lags $p$ is resolved by some tests that are used to detect these optimal lag lengths which are: a) the Schwartz Information Criterion, b) the Akaike Information Criterion, c) Hannan-Quinn Criterion and d) the Modified forms of these criteria.

### 3.2.2 Generalized Least Squares de-trending Dickey-Fuller test

This test is a modified version of the ADF regression test in which the data are de-trended so that explanatory variables are “taken out” of the data prior to running the test regression.

$$d(y_t \mid \alpha) = \begin{cases} y_t & \text{if } t = 1 \\ y_t - ay_{t-1} & \text{if } t > 1 \end{cases}$$  \hspace{1cm} (5)

Afterwards, we consider an OLS regression of the quasi-differenced data $d(y_t \mid \alpha)$ on the quasi-differenced $d(x_t \mid \alpha)$.

$$d(y_t \mid \alpha) = d(x_t \mid \alpha)\hat{\delta}(\alpha) + \eta_t$$  \hspace{1cm} (6)

where $x_t$ contains either a constant, or a constant and trend, while $\hat{\delta}(\alpha)$ is the OLS estimates from this regression. What is needed next is a value for $\alpha$. The use of $a = \bar{\alpha}$ is recommended by ERS (1996) where:

$$\bar{\alpha} = \begin{cases} 1 - 7/T & \text{if } x_t = \{1\} \\ 1 - 13.5/T & \text{if } x_t = \{1, t\} \end{cases}$$  \hspace{1cm} (7)

Now the GLS de-trended data $y_t^{d}$ is defined, using the estimates associated with the $\bar{\alpha}$:

$$y_t^{d} = y_t - x_t \hat{\delta}(\bar{\alpha})$$  \hspace{1cm} (8)
Then the GLS-DF test involves estimating the standard ADF test Eq. (4), after substituting the GLS de-trended $y_t^d$ for the original $y_t$:

$$\Delta y_t^d = \alpha y_{t-1}^d + \beta_1 \Delta y_{t-1}^d + \ldots + \beta_p \Delta y_{t-p}^d + u_t$$  \hspace{1cm} (9)$$

Since the $y_t^d$ are de-trended, the $x_t$ is not included in the GLS-DF equation. Similar to the ADF test, the $t$-ratio for $\hat{\alpha}$ is considered from this test equation.

### 3.2.3 Phillips and Perron test

Phillips and Perron (1988) suggest an alternative, non-parametric, method to control for serial correlation when testing for a unit root. Primarily, the PP test estimates Eq. (1) of the ADF test, while afterwards, modifies the $t$-ratio of the $\alpha$ coefficient. This helps the asymptotic distribution not to be affected. The subsequent statistic illustrates the PP method:

$$t_{\hat{\alpha}} = t_{\alpha} \left( \frac{\gamma_0}{s} \right)^{1/2} - \frac{T(f_0 - \gamma_0)(se(\hat{\alpha}))}{2f_0^{1/2}s}$$  \hspace{1cm} (10)$$

where $t_{\alpha}$ and $\hat{\alpha}$ the $t$-ratio of $\alpha$ as well as the estimate, respectively. The standard error coefficient is presented as $se(\hat{\alpha})$ whereas $s$ is the standard error. Additionally, $\gamma_0$ is considered as the estimation of the error variance in Eq. (1). As far as the remaining term, $f_0$, is concerned, it is an estimator of the residual spectrum at frequency zero.

### 3.3 Stationarity test

#### 3.3.1 Kwiatkowski-Phillips-Schmidt-Shin test

There is a significant difference between the Kwiatkowski-Phillips-Schmidt-Shin (1992) test [KPSS hereafter] and those unit root tests that have been already described above. It is the null hypothesis that makes this particular difference under which the series $y_t$ is assumed to be (trend-) stationary. More precisely, the KPSS statistic is based on the residuals from the OLS regression of $y_t$ on the exogenous variables $x_t$:

1. The $\gamma_0$ term is calculated as $(T-k)s^2/T$, where $k$ is the number of regressors.
\[ y_i = x_i' \delta + u_i \]  

(11)

The LM statistic is defined as:

\[ LM = \sum_i S(t)^2 / (T^2 f_0) \]  

(12)

where \( f_0 \) is the estimator of the residual spectrum at frequency zero and in which \( S(t) \) is a cumulative residual function:

\[ S(t) = \sum_{r=1}^{i} \hat{u}_r \]  

(13)

which is a function based on the residuals \( \hat{u}_i = y_i - x_i' \tilde{\delta}(0) \). Something to be mentioned concerns the estimator of \( \delta \) in the KPSS test which differs from \( \delta \) used by the GLS as in the former, it is based on a regression that involves the original data, while in the latter on a regression that involves quasi-differenced data.

3.4 Unit root tests with breaks

A commonly faced problem, concerning the aforementioned unit root tests, is that they do not allow the possibility of a structural break. This is the reason why we test for the existence of one structural break in the series. More specifically, in the following steps are presented the Zivot and Andrews (1992), and the Perron (1989) unit root tests for one break.

3.4.1 Zivot-Andrews unit root test for one break

The Zivot and Andrews (1992) unit root test [henceforth, ZA] allows an endogenous identification of a possible structural break in the data. Under the null hypothesis, the ZA test assumes the presence of a unit root, whereas stationarity around a structural break, which takes place at an unknown time, is suggested by the alternative hypothesis. This unknown time, \( TB \), can be endogenously determined so as to be the least favorable moment in relation to the controlled null hypothesis. Zivot and Andrews (1992) presented three versions of the test which differed in how they modeled the structural break in the time trend under the alternative hypothesis. More specifically, the variable under consideration is represented by \( \{y_i\}_{t=1}^{T} \) for the sample size \( T \) in order to define the dummies \( DU_i = J(t>TB) \) and \( DT_i = (t-TB) \)
\( J(t>T_B) \), where \( t = 1, \ldots, T \) and \( J(.) \) the position function\(^2\). These particular three versions of the ZA test are presented below:

Model A: \( \Delta y_t = \mu + \beta t + 9 DU_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \epsilon_t \) \( (14) \)

Model B: \( \Delta y_t = \mu + \beta t + \gamma DT_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \epsilon_t \) \( (15) \)

Model C: \( \Delta y_t = \mu + \beta t + 9 DU_t + \gamma DT_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \epsilon_t \) \( (16) \)

Model A allows only for one structural break in the intercept, model B only one structural break in the time trend, whereas model C, which is less restrictive than the other two, allows the structural break to take place in both intercept and time trend. So, depending on the model that has been adopted in each case, the null hypothesis as well as the alternative one are as follows:

\[ H_0 : y_t = \mu + y_{t-1} + \epsilon_t \]

\[ H_1 : \text{Model A or B or C} \]

The above null hypothesis is rejected if the \( t \)-statistic of the \( \alpha \) coefficient is greater than the corresponding asymptotic critical value provided by Zivot and Andrews (1992). Last but not least, something to be mentioned is that the ZA unit root test under the break as well as the others that follow are examined only in the levels.

3.4.2. Perron unit root test for one break

Perron (1989) discovered that the ignorance of a structural break can lead to incorrect results and accordingly to the acceptance of the null hypothesis as in the case of Dickey and Fuller (1979). He proposed the Perron unit root test which is characterized by a single exogenous structural break with three alternative models: the first, which allows for a break in the level (or else intercept) of the series, and it is characterized as ‘crash’ model; the second which permits for a break in the slope (or the growth rate) and last but not least the model that allows an amendment both in the level as well as in the slope of the series to occur simultaneously. A modified ADF unit root test is used by Perron (1989). Dummy variables

\(^2\) The position function for the variable \( DU_t \) attributes the value 1 if \( t > TB \) and 0 otherwise, while for the variable \( DT_t \) returns the value \( (t-TB) \) if \( t > TB \) and 0 otherwise.
are included in this modification to account for one structural break. The selection of the break point becomes independently as far as the data are concerned, while it is fixed (or else exogenous). What is more, in this particular test a break is allowed under both the null and alternative hypothesis but such tests are consequently, less powerful than the standard ADF test when there is no break.

3.5 The KSS non-linear unit root test

The non-linear unit root test that proposed by Kapetanios, Shin and Snell (2003) [KSS, hereafter] and employed by Zhou et al. (2008), presented a new technique regarding the null hypothesis of a unit root against an alternative one of non-linear stationary smooth transition. The KSS test is based on the exponential smooth transition autoregressive (ESTAR) specification as follows:

\[ \Delta q_t = \gamma q_{t-1} \left[ 1 - \exp \left\{ -\theta q_{t-1}^2 \right\} \right] + \varepsilon_t, \quad \theta \geq 0 \]  

(17)

where \( q_t \) is the real exchange rate and \( \left[ 1 - \exp \left\{ -\theta q_{t-1}^2 \right\} \right] \) is the exponential transition function that presents the non-linear adjustment in the test. Since the null hypothesis of a unit root in \( q_t \) indicates that \( \theta = 0 \), we test

\[ H_0 : \theta = 0 \]

against the alternative one

\[ H_A : \theta > 0. \]

Due to the fact that \( \gamma \) which is included in Eq. (14) is not identified under the null hypothesis, \( H_0 : \theta = 0 \) cannot be tested directly. In order to cope with this matter, KSS recommend reparameterise Eq. (14) by computing a first-order Taylor series approximation so as to obtain the next supportive regression:

\[ \Delta q_t = \delta q_{t-1}^3 + \varepsilon_t \]  

(18)
In an attempt to attain a more general case in which the errors are serially correlated, the above regression can be converted into a more extended form:

\[ \Delta q_t = \sum_{j=1}^{p} \rho_j \Delta q_{t-j} + \delta q_{t-1}^3 + \epsilon_t \]  

with \( p \) augmentations to be used so as to correct for serially correlated errors. Thus, the null hypothesis of non-stationarity to be tested with either Eq. (15) or (16) is:

\[ H_0 : \delta = 0 \]

against the alternative

\[ H_A : \delta < 0 \]

while the \( t \)-statistic is

\[ t_{NL} = \frac{\hat{\delta}}{se(\hat{\delta})} \]  

(20)

What KSS demonstrate is that the \( t_{NL} \) does not have an asymptotic standard normal distribution, as well as they tabulate the asymptotic critical values of the \( t_{NL} \) statistics through the stochastic simulations.

The KSS test modifies the data according to the appropriate case in order to accommodate stochastic procedures with non-zero means and/or linear deterministic trends. As a consequence, in the case that the data has a non-zero mean, the demeaned data are used whereas in a case where non-zero mean and non-zero linear trend are detected, the demeaned and de-trended data are used (Christidou and Panagiotidis, 2010).

3.6 The VAR model, Cointegration and VECM

There are several methodologies for the investigation of whether a system of economic variables is cointegrated. Namely, some of them are the Engle and Granger (1987) approach, the Johansen and Juselius (1990) approach as well as the Autoregressive Distributed Lag (ARDL) procedure to cointegration that are presented below.
3.6.1 The Vector Autoregression (VAR) Model

The Vector Autoregression (VAR) model is one of the most successful and flexible models concerning the analysis of the multivariate time series. In case that cointegration has not been detected, VAR as well as Granger’s causality are used to determine whether the past, and the present values of the independent variables provide some useful information to forecast the dependent variables in the short term. A VAR approach successfully avoids endogeneity problems since treats to all the variables as being endogenous. A levels VAR model which can be augmented with intercepts is given by the next form:

\[ y_t = \alpha_0 + \sum_{j=1}^{p} A_j y_{t-j} + \epsilon_t \]  

(21)

where \( p \) is the maximum number of lagged observations, \( y_t \). The series can be I(0). \( \alpha_0 \) is a vector of constant terms or \( \alpha_0 = \left[ \alpha_{CO_2}, \alpha_{EC}, \alpha_{GDP} \right] \), and \( A_j \) is the matrix of VAR parameters for lag j. The vector of error terms are \( \epsilon_t = \left[ \epsilon_{CO_2}, \epsilon_{EC}, \epsilon_{GDP} \right] \sim IN(0, \Omega) \).

To be more explanatory, we assume two models for time series \( y_t \) as follows:

\[ \Delta y_t = \omega_{11} + \sum_{i=1}^{p} \alpha_{1i} \Delta y_{t-i} + \sum_{j=1}^{p} \beta_{1j} \Delta y_{t-j} + v_t \]  

(22)

\[ \Delta y_j = \omega_{21} + \sum_{i=1}^{p} \alpha_{2i} \Delta y_{t-i} + \sum_{j=1}^{p} \beta_{2j} \Delta y_{t-j} + v_2 \]  

(23)

where \( p \) is the maximum number of lagged observations, \( \omega, \alpha, \text{and} \beta \) are estimated and \( v \)’s are error terms. In the first equation, if the past as well as the present values of the \( y_{t-j} \) provide some useful information in order to forecast \( y_t \) at time \( t \), it is said that \( y_{t-j} \) Granger causes \( x_t \) while unidirectional causality runs from \( y_{t-j} \) to \( y_t \). The same procedure is followed for the second equation as well. Now, if \( y_{t-j} (y_{t-j}) \) and \( y_t \) are jointly determined and therefore affected at the same time, bi-directional causality exists between the two variables known as ‘feedback causality’. Conversely, if \( y_{t-j} (or \ y_{t-j}) \) and \( y_t \) have no causality, this condition is determined as ‘neutrality’ (Chang, et al., 2011).
3.6.2 Cointegration and the Vector Error Correction Model (VECM)

The concept of cointegration can be properly defined either as a common stochastic, or as a systematic co-movement between two or more variables over the long-run. A number of tests such as the trace test and the maximum eigenvalue test are used to discover the existence of cointegration and if the method of estimation is the OLS or the maximum likelihood, the results obtained are similar. In case that the results indicate evidence of cointegration within the variables, this shows that the underlying variables enact a systematic co-movement in the long-run. When such a long-run relationship is evident, the VECM should be applied.

The VECM was, firstly, introduced by Sargan (1964) and became more popular by Engle and Granger (1987) and Granger (1988), while refined later on by Hendry and Juselius (2000) who gave emphasis on the importance of correct specification. According to Granger’s (1988) arguments, if variables are non-stationary but cointegrated and become stationary after the first difference, it seems essential to estimate a VECM for the multivariate causality test.

3.6.1 Johansen approach to cointegration

The Johansen and Juselius’s (1990) multivariate cointegration methodology is used for investigating the presence of cointegration. The Johansen cointegration tests are performed for the VARs at levels. It is considered that the Johansen and Juselius’s (1990) maximum likelihood is complementary by the ARDL bounds testing approach since it provides a sensitivity test on the results. Let’s consider a VAR of order $p$:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + Bx_t + \varepsilon_t$$

(24)

where $y_t$ is a $k$-vector of non-stationary I(1) variables, $x_t$ is a $d$-vector of deterministic variables and $\varepsilon_t$ is a vector of innovations. This VAR can be rewritten as

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i y_{t-i} + Bx_t + \varepsilon_t$$

(25)

where:

$$\Pi = \sum_{i=1}^{p} A_i - I, \quad \Gamma_i = - \sum_{j=i+1}^{p} A_j$$

(26)
Granger’s representation theorem states that if the coefficient matrix \( \Pi \) has reduced rank \( r < k \), then there exist \( k \times r \) matrices \( \alpha \) and \( \beta \) each with rank \( r \) such that \( \Pi = \alpha \beta' \) and \( \beta'y \) is \( I(0) \). \( r \) is the number of co-integrated relations or else, the cointegration rank and each column of \( \beta \) is the cointegrating vector. \( \Gamma \) denotes the coefficient matrix, \( p \) indicates the lag-length and lastly \( \varepsilon_t \) is the residual matrix. The purpose of the Johansen’s cointegration method is to estimate \( \Pi \) matrix from an unrestricted VAR as well as to test whether the restrictions implied by the reduced rank of \( \Pi \) can be rejected. The whole number of the variables in this equation is considered as potentially endogenous. The trace and the maximal eigenvalue tests can be used in order for the cointegrated rank to be found. More specifically, the trace value tests the null hypothesis of \( r \) cointegration relations against the alternative of \( k \) co-integrating relations, where \( k \) is the number of endogenous variables for \( r = 0, 1, \ldots, k - 1 \). The alternative of \( k \) is related to the case where none of the series has a unit root whereas a stationary VAR may be specified in terms of the levels of all series. The trace statistic for the null hypothesis of \( r \) is calculated as follows:

\[
LR_r(r | k) = -T \sum_{i=r+1}^{k} \log(1 - \lambda_i) \tag{27}
\]

where \( \lambda_i \) is the largest \( i \)-th eigenvalue of the \( \Pi \) matrix in Eq. (28). On the other hand, the maximum eigenvalue statistic tests the null hypothesis of \( r \) against the alternative of \( r + 1 \) cointegrated relations. This particular test statistic is computed as:

\[
LR_{\max}(r | r + 1) = -T \log(1 - \lambda_{r+1}) = LR_r(r | k) - LR_r(r + 1 | k) \tag{28}
\]

for \( r = 0, 1, \ldots, k - 1 \).

Moreover, the lag-length of the unrestricted VAR structure in the equation is selected on the basis of several criteria, however, the AIC, Schwarz Bayesian Criterion (SBC) and the adjusted likelihood ratio (LR) are the most commonly used. It is argued that the critical values of Johansen and Juselious (1990) should be scaled in such a way so as to allow more appropriate statistical inference when small sample sizes exist. After all, the implied scaling factor is given by the next formula:

\[
SF = T/(T - n_\varepsilon) \tag{29}
\]
where \( T \) is the number of observations, \( n \) is the number in the estimated system and \( \xi \) is the lag parameter (Halicioglu, 2009).

### 3.6.2 Engle and Granger approach to cointegration

Engle and Granger (1987) representation theorem is a univariate cointegration approach which establishes that causality in at least one direction must exist between a number of cointegrated variables. Engle and Granger (1987) state that if two variables, for instance, \( X \) and \( Y \), are both non-stationary, then it would be expected that a linear combination of \( X \) and \( Y \) would be a random walk. Nevertheless, a particular combination of these two variables \( Z = X - bY \) could result in stationarity. In such a case that the aforementioned property holds true, the \( X \) and \( Y \) are co-integrated (Yoo, 2006).

To get in more details, Engle and Granger (1987) test uses a parametric, ADF approach and estimates a \( p \)-lag augmented regression of the following form:

\[
\Delta \hat{u}_t = (\rho - 1)\hat{u}_{t-1} + \sum_{j=1}^{p} \delta_j \Delta \hat{u}_{t-j} + u_t
\]  

(30)

The number of lagged differences \( p \) should increase to infinity with the (zero-lag) sample size \( T \) but at a rate slower than \( T^{1/3} \).

Two standard ADF test statistics are considered, one that is based on the \( t \)-statistic for testing the null hypothesis of non-stationarity \( (\rho = 1) \) and the other based directly on the normalized autocorrelation coefficient \( \hat{\rho} - 1 \):

\[
\hat{\tau} = \frac{\hat{\rho} - 1}{se(\hat{\rho})}
\]

\[
\hat{z} = \frac{T(\hat{\rho} - 1)}{\left(1 - \sum_j \hat{\delta}_j\right)}
\]

(31)

where \( se(\hat{\rho}) \) is the usual OLS estimator of the standard error of the estimated \( \hat{\rho} \)

\[
se(\hat{\rho}) = \hat{s}_u \left(\sum_j \hat{u}_{t-1}^2\right)^{-1/2}
\]

(32)
The test statistics corresponding to Eq. (33) are the following:

\[
\hat{t} = \frac{\hat{\rho}^* - 1}{se(\hat{\rho}^*)} \quad (33)
\]

\[
\hat{z} = T \left( \hat{\rho}^* - 1 \right)
\]

where

\[
se(\hat{\rho}^*) = \hat{\sigma}_\omega^{1/2} \left( \sum_{t} \hat{\omega}_{t-1}^2 \right)^{-1/2} \quad (34)
\]

On the other hand, if the two variables are non-stationary but cointegrated, then a more comprehensive causality test should be adopted based on the ECM. The ECM is used to estimate the short-run causal relationship. Hence, a VECM must be formulated to reintroduce the lost information in the differencing process, and by this means to allow for long-run equilibrium and short-run dynamics as well. Alternatively, if \( X \) and \( Y \) are both non-stationary as well as their linear combination of the time-series is non-stationary, the standard Granger’s causality is the most appropriate and valid technique to be used.

3.6.3 The ARDL approach to cointegration

The Autoregressive Distributed Lag (ARDL) cointegration analysis, also known as the ARDL bounds testing approach that developed by Pesaran and Shin (1998) and Pesaran et al. (2001) is a method that has numerous econometric advantages in comparison with other co-integration procedures such as Eagle and Granger (1987) and Johansen and Juselius (1990) approaches. It could also be characterized as complementary to the Johansen’s maximum likelihood method. In particular, these advantages can be summarized as follows: i) there is no need for all the variables included in the system to be of equal order of integration (they can be, either I(0), or I(1), or fractionally integrated) as well as the problems raised by unit root pre-testing can be significantly avoided; ii) it constitutes an efficient estimator even if the sample sizes are small (Narayan, 2005) while possible endogeneity problems of the regressors are avoided; iii) the long- and short-run parameters are estimated simultaneously while it is possible that the variables may have different optimal lag-lengths, and iv) it employs a single reduced form equation (Ozturk and Acaravci, 2010).
The ARDL bounds testing approach involves two steps in order to estimate the long-run relationship. The first one is referred to the investigation of the existence of long-run relationship between all the variables included in the equation (in our specific study is the CO₂ emissions, the energy consumption and the GDP). This happens by estimating the unrestricted error correction model by OLS method as follows:

\[
\Delta GDP_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i \Delta GDP_{t-i} + \sum_{i=1}^{n} \alpha_2 \Delta CO_{2t-i} + \sum_{i=1}^{n} \alpha_3 \Delta EC_{t-i} + \alpha_4 GDP_{t-1} + \alpha_5 CO_{2t-1} + \alpha_6 EC_{t-1} + \varepsilon_t
\]  

where \(\Delta\) is the first difference operator and \(\varepsilon_t\) is the white noise term. What is more, the ARDL bounds testing approach is based on the joint \(F\)-statistic or Wald statistic that tests the null hypothesis of no cointegration (Ozturk and Acaravci, 2010):

\[H_0 : \delta_r = 0\]

against the alternative one

\[H_1 : \delta_r \neq 0, \quad r = 1, 2, 3, 4\]  

Pesaran et al. (2001) provide two sets of critical bounds value for all the classifications of the regressors into I(0), I(1) or mutually cointegrated. In case that the calculated \(F\)-statistics exceeds the upper level of the band, the null hypothesis is rejected, indicating cointegration. On the other hand, if the calculated \(F\)-Statistics lies below the upper critical bounds’ value, the null hypothesis cannot be rejected, and this implies the absence of cointegration. Lastly, if it lies among the bounds, a conclusive inference is impossible without knowing the order of integration of the basic regressors. However, according to Narayan’s (2005) arguments, these critical values are inappropriate whenever the sample size is small, or in other words, the data involved are annual (Wolde-Rufael, 2010).

The second step concerns the estimation of the next long-run and short-run models that are presented in Eq. (35) and Eq. (36) whether long-run relationship (in other words, cointegration) is evident between the underlying variables. When the existence of cointegration relationship is identified, it is time for the optimal ARDL specification model as presented below:
\[ GDP_t = b_0 + \sum_{i=1}^{b_1} b_i GDP_{i-t} + \sum_{i=0}^{b_2} b_i CO_{2t-i} + \sum_{i=0}^{b_3} b_i EC_{t-i} + u_t \] 

(37)

The long-run multipliers can be obtained as non-linear functions of the parameter estimated of the above equation. More specifically, the long-run multipliers will be:

\[ a_0 = b_0 \left( 1 - \sum_{i=1}^{b_1} b_i \right) \] 

(38)

and

\[ a_j = b_{i_j} \left( 1 - \sum_{i=1}^{b_1} b_{i_j} \right) \] 

(39)

with \( j=1,\ldots,5 \) and \( m=2,\ldots,6 \)

The final step of the procedure is to estimate the short-run dynamic coefficients for the optimal ARDL model via the ECM:

\[ \Delta GDP_t = d_0 + \sum_{i=1}^{d_1} d_i GDP_{i-1} + \sum_{i=1}^{d_2} d_i CO_{2t-i} + \sum_{i=1}^{d_3} d_i EC_{t-i} + d_4 \psi_{t-1} + e_t \] 

(40)

where \( \psi_{t-1} \) is the error correction term resulting from the verified long-run equilibrium relationship (it should be a statistically significant coefficient with a negative sign) and \( d_j \) is a parameter that indicates the speed of adjustment to the equilibrium level after a shock. Furthermore, Pesaran and Pesaran (1997) pointed out how important is to ascertain the constancy of the long-run multipliers by testing the aforementioned ECM for the stability of its parameters. For such as purpose, the most commonly used tests are the cumulative sum (CUSUM) and the cumulative sum of squared (CUSUMQ) both of which are introduced by Brown et al. (1975) [Dergiades and Tsoulfidis, 2008].

Because of the small sample size, the model is selected by the usage of the SBC as suggested by Pesaran and Pesaran (1997) due to the fact that the SBC selects the smallest possible lag-length whereas the AIC selects the maximum relevant lag-length.
3.7 The GARCH BEKK Model

The GARCH BEKK (1,1) model is used in order to specify the variance and covariance equations. It is used to test for the second moment filtering at GARCH residuals. The multivariate BEKK GARCH model consists of the three variables under investigation, the CO₂ emissions, the energy consumption and the economic growth. The three conditional mean equations can be defined as follows:

\[
\Delta CO_t = c_{co} + \sum_{j=1} a_{co,j} \Delta CO_{t-j} + \sum_{j=1} b_{co,j} \Delta EC_{t-j} + \sum_{j=1} \gamma_{co,j} \Delta GDP_{t-j} + \epsilon_{co,t} \tag{41}
\]

\[
\Delta EC_t = c_{EC} + \sum_{j=1} a_{EC,j} \Delta EC_{t-j} + \sum_{j=1} b_{EC,j} \Delta CO_{t-j} + \sum_{j=1} \gamma_{EC,j} \Delta GDP_{t-j} + \epsilon_{EC,t} \tag{42}
\]

\[
\Delta GDP_t = c_{GDP} + \sum_{j=1} a_{GDP,j} \Delta GDP_{t-j} + \sum_{j=1} b_{GDP,j} \Delta CO_{t-j} + \sum_{j=1} \gamma_{GDP,j} \Delta EC_{t-j} + \epsilon_{GDP,t} \tag{43}
\]

where, \( \Delta CO, \Delta EC \) and \( \Delta GDP \) are the growth rates of the CO₂ emissions, the energy consumption and the economic growth. \( \epsilon_{co,t}, \epsilon_{EC,t} \) and \( \epsilon_{GDP,t} \) are the error terms and \( c_j, a_j, b_j, \gamma_j, \phi_j, \xi_j, \psi_j \) are the parameters that need to be estimated.

With regard to a bivariate BEKK GARCH (1,1) model and considering the available information as \( \Omega_{t-1} \), the conditional variance and covariance equations can be obtained as functions of the past errors that are presented below:

\[
z_{xx} = c_{11} + c_{12} + b_{11} z_{x,t-1} + 2b_{12} z_{y,t-1} + b_{21} z_{x,t-1} + b_{22} z_{y,t-1} + a_{11} \epsilon_{x,t-1} \epsilon_{x,t-1} + a_{21} \epsilon_{x,t-1} \epsilon_{y,t-1} + a_{22} \epsilon_{y,t-1} \epsilon_{y,t-1} \tag{44}
\]

\[
z_{xy} = c_{21} + c_{22} + b_{11} z_{x,t-1} + 2b_{12} z_{y,t-1} + b_{21} z_{x,t-1} + b_{22} z_{y,t-1} + a_{11} \epsilon_{x,t-1} \epsilon_{y,t-1} + a_{21} \epsilon_{x,t-1} \epsilon_{y,t-1} + a_{22} \epsilon_{y,t-1} \epsilon_{y,t-1} \tag{45}
\]

\[
z_{yx} = c_{11} + c_{12} + b_{11} z_{x,t-1} + (b_{11} b_{21} + b_{12} b_{21}) z_{y,t-1} + b_{21} z_{x,t-1} + b_{22} z_{y,t-1} + a_{11} a_{22} \epsilon_{x,t-1} \epsilon_{x,t-1} + a_{21} \epsilon_{x,t-1} \epsilon_{y,t-1} \tag{46}
\]

Conversely, equations (44)-(46) can be written in compact form by using matrix notation as follows:

\[
Z_t = C^T C + B^T Z_{t-1} B + A^T \epsilon_{t-1} \epsilon_{t-1} A \tag{47}
\]
where, $Z_t$ is the positive definite 2x2 conditional variance-covariance matrix of the errors, $C$ is 2x2 upper triangular matrix of coefficients and lastly, $B$ and $A$ are also unrestricted matrices of coefficients (Tsintzos and Dergiades, 2010).

3.8 Testing for non-linearity in the series

It is of great importance to mention that linear approaches to causality testing can result in problems such as the low power detecting from certain kinds of non-linear causal relations. This is the reason why the following approach becomes essential to test for non-linearity in the series.

3.8.1 The BDS test

The Brock, Dechert and Scheinkman (BDS) test is applied as suggested by Brock et al. (1996) in order to test for non-linear causality and identify potential deviations from the assumption of independence. The BDS is a test that can be implemented to the residuals derived from the de-linearization of the series (e.g. residuals computed from a VAR specification), to ascertain whether or not these residuals are independent and identically distributed (the so-called i.i.d. assumption). According to this, it should be demonstrated, for any particular pair of observations, that the probability of their distance being less than or equal to $\theta$ (where $\theta$ is a randomly selected small positive number), remains constant.

The BDS test, given for instance the $\kappa$-dimensional $Z_t$ series, identifies among all the available sample sets of a pre-selected length, those sets that satisfy the $\theta$ condition, through the use of the following correlation integral:

$$
\hat{C}_{\kappa,n}(\theta) = \frac{2}{(n-\kappa+1)(n-\kappa)} \sum_{s=1}^{n-\kappa} \sum_{t=s+1}^{n-\kappa} \prod_{j=0}^{\kappa-1} I(Z^\kappa_{ts+j}, Z^\kappa_{ts+j})
$$

(48)

where, the indicator function $I(Z^\kappa_{ts+j}, Z^\kappa_{ts+j})$ takes on the value of 1 if $\|Z^\kappa_t, Z^\kappa_s\| \leq \theta$ and 0 otherwise, $\|Z^\kappa_t, Z^\kappa_s\|$ denotes the Euclidean distance between $Z^\kappa_t$ and $Z^\kappa_s$.

In order to test the assumption of independence, Brock et al. (1996) showed that the $B$ Statistic defined as

42
follows the standard normal distribution. Where, $S_{\kappa,n}(\theta)$ is the standard deviation estimator (Dergiades et al., 2011).

3.9 Parametric Causality Tests

3.9.1 Granger causality

The first method proposed for testing the direction of causality, was by Granger (1969). The Granger’s representation theorem recommends that Granger causality is evident in at least one direction if cointegration exists among the variables providing that there is integration of order one on these variables. In a simpler way, a time series $X$ is said to Granger cause another time series $Y$ if the prediction error of current $Y$ declines by using past values of $X$ additionally to past values of $Y$. The time series of the variables need to be stationary otherwise spurious causality results can be yielded. With regard to cointegration, if there is an absence of cointegration the Granger’s causality is performed as a VAR in first differences form. On the other hand, according to Engle and Granger (1987), the presence of cointegration on a Granger causality test, which is conducting on the variables’ first differences by means of a VAR, will lead to misleading results. Hence, the long-run relationship could be captured by the inclusion of an additional variable to the VAR system such as the error correction term. As a result, an augmented form of the Granger causality test with the error correction term involved is formulated in a multivariate $p$-th order VECM as the next one (Halicioglu, 2009).

\[
B = (\sqrt{n} - \kappa + 1) \frac{\hat{C}_{\kappa,n}(\theta) - \hat{C}_{1,n-k+1}(\theta)^X}{S_{\kappa,n}(\theta)} \rightarrow N(0,1) \tag{49}
\]

\[
\begin{align*}
(1 - L) \begin{bmatrix}
CO_{2t} \\
EC_t \\
GDP_{t-1}
\end{bmatrix} &= \begin{bmatrix}
c_1 \\
c_2 \\
c_3
\end{bmatrix} + \sum_{i=1}^{p} (1 - L) \begin{bmatrix}
d_{1i} \\
d_{2i} \\
d_{3i}
\end{bmatrix} \begin{bmatrix}
CO_{2t-1} \\
EC_{t-1} \\
GDP_{t-2}
\end{bmatrix} + \begin{bmatrix}
\lambda_1 \\
\lambda_2 \\
\lambda_3
\end{bmatrix} \begin{bmatrix}
\psi_{t-1} \\
\psi_{t-2} \\
\psi_{t-3}
\end{bmatrix} + \begin{bmatrix}
\omega_{t1} \\
\omega_{t2} \\
\omega_{t3}
\end{bmatrix} \tag{50}
\end{align*}
\]
where \((1-L)\) is the lag operator and \(\Psi_{t-1}\) is the error correction term (ECT). The residual terms \(\omega_{1t}, \omega_{2t}, \omega_{3t}\) and \(\omega_{4t}\), are independently and normally distributed with zero mean and constant variance. The AIC or the SBC is used for the lag selection. Moreover, there are two ways that the causal relationship can be examined via the above equation; firstly, the short-run or weak Granger causality is detected by checking the statistical significance of the lagged differences of the variables for each vector through the \(F\)-statistics or the Wald test; secondly, the long-run causalities are identified by examining the statistical significance of the lagged ECT in the equation via the \(t\)-test or Wald test (Halicioglu, 2009).

3.9.2 Toda-Yamamoto causality test

The Toda-Yamamoto (1995) [TY hereafter] procedure is an especially appealing test since it detects for long-run Granger causality without requiring a pre-testing for cointegration and thus enables feedback effects through several lags. What is more, the TY procedure has no loss of information due to differencing since it involves a VAR in levels. It is considered that the TY procedure is a modified Wald test that is to test restrictions on the parameters of the VAR\((k)\) model (where \(k\) is the optimal lag length). An asymptotic \(\chi^2\) distribution with \(k\) degrees of freedom \((\chi^2(k))\) is followed by the statistic. The procedure requires augmenting the VAR\((k)\) in levels with \(d\), where \(d\) is the maximal order of integration of the variables in the system. After several diagnostic tests on the resulting VAR\((k+d)\), a Wald test is conducted on the first \(k\) parameters. If the first \(k\) parameters are identified as statistically significant, the null hypothesis of non-causality is rejected. Several criteria are used in order to determine the optimal lag length, \(k\) (Soytas et al., 2007).

The TY is considered a \(n\)-vector time series \(Z_t\) generated by the \(k\)-th order VAR model as follows:

\[
Z_t = \Phi_0 + \Phi_1 t + \Phi_2 t^2 + \Pi_1 Z_{t-1} + \ldots + \Pi_k Z_{t-k} + E_t, \quad t = 1, \ldots, T
\]

where \(E_t \sim N(0, \Omega)\) denotes white noise residuals; \(Z_t = (LGDP_t, LCO_2_t, LEC_t)\); and \(t\) represents a deterministic time trend. Economic hypotheses can be expressed as restrictions on the coefficients in the model in accordance with the following (Lee, 2006):

\[
H_0: F(\pi) = 0
\]
where $\pi = \text{vec}(P)$ is a vector of the parameters in equation (1). $P = (\Pi_1, \ldots, \Pi_k)$ and $F(\cdot)$ is a twice continuously differentiable $m$-vector valued function (Lee, 2006).

### 3.9.3 The Hsiao two-stage causality method

The Hsiao two-step causality method (1979) is a version of the Granger causality procedure that combines the Akaike’s (1969) Final Prediction Error (FPE) with the Granger causality test, through a VECM approach, in order to determine the optimum number of own-lagged and cross-lagged terms as well as the causality direction of two or more variables. The FPE is a rule that rewards good fit from the one hand, but penalizes the losses concerning the degrees of freedom. Hsiao’s method consists of two steps. The first one is to estimate the equation so as to compute the residual sum of squares by varying the lag order $(l_{11})$ from 1 to $L_{11}$.

\[
\Delta Y_t = a_{11} + \sum_{i=1}^{l_{11}} \beta_{11i} \Delta Y_{t-i} + u_{11t}
\]  

(52)

The FPE($l_{11}$), which represents the lag consideration, is estimated by

\[
FPE(l_{11}) = \left[ \frac{T + l_{11} + 1}{T - l_{11} - 1} \right] \frac{RSS(l_{11})}{T}
\]  

(53)

where $T$ is the sample size and RSS is the residuals sum of squares from the first equation. Hence, in case that $L_{11}$ is set at seven, there are seven FPEs. Moreover, the smallest value of $FPE(l_{11})$ determines the optimal lag ($l'_{11}$) (Yoo and Kwak, 2010). The second step is to estimate the equation:

\[
\Delta Y_t = a_{12} + \sum_{j=1}^{l_{11}} \beta_{12j} \Delta Y_{t-j} + \sum_{j=1}^{l_{12}} \beta_{2j} \Delta X_{t-j} + u_{12t}
\]  

(54)

For the additional variable $X$, the lag order is from 1 to $L_{42}$ and calculates the modified-two dimensional FPE as follows:

\[
FPE(l'_{11}, l_{12}) = \left[ \frac{T + l'_{11} + l_{12} + 1}{T - l'_{11} - l_{12} - 1} \right] \frac{RSS(l'_{11}, l_{12})}{T}
\]  

(55)
Once again, the smallest value of $FPE(l_{11}, l_{12})$ determines the optimal lag ($l_{12}$). Apparently, the appropriate lags ($l_{11}, l_{12}$) are evaluated by this way. Whether $FPE(l_{11}, l_{12})$ is smaller than $FPE(l_{11})$, $X$ Granger causes $Y$. Consequently, the combination of the FPE criterion and the Granger’s definition of causality in the Hsiao’s method, allows two variables to enter into the equation with different numbers of lags. Hence, there is a reduction in the number of lags to be estimated. Additionally, all the series need to be stationary in order to evaluate the Hsiao’s version of Granger’s causality, whereas if any found to be non-stationary, the first differences must be taken and has to be re-estimated with differenced data (Yoo, 2006).

3.10 Non-parametric Causality Tests

3.10.1 Hiemstra and Jones test

The Hiemstra and Jones (1994) test [henceforth, H&J] is a modified form of the Baek and Brock (1992) test for conditional independence, which has critical values that are based on the asymptotic theory. In order for the test statistic to be propelled, the null hypothesis needs to be restated in terms of ratios of joint distributions. More specifically, let’s consider two strictly stationary and weakly dependent time series, $G_t$ and $E_t$, the subsequent definitions are evident: let $Z_t^\kappa$ to be the $\kappa$-length lag vector of $G_t$, $E_t^\ell$ the $\ell$-length lag vector of $E_t$ and lastly, $G_t^{lg}$ the $l_g$-length lag vector of $G_t$, with $l_c, l_g \geq 1$. Regarding that the null hypothesis is in fact a proposition about the invariant distribution of the $(l_c + l_g + \kappa)$-dimensional vector $X_t = (E_t^\ell, G_t^{lg}, Z_t^\kappa)$, the time subscript is dropped. It is also taken for granted that $\kappa$ is equal to 1 as well as we set $l_c = l_g = 1$. Consequently, taking into consideration the abovementioned assumptions and definitions, the null hypothesis of no causality should satisfy the following condition:

$$\frac{f_{E,G,Z}(e,g,z)}{f_{E,G}(e,g)} = \frac{f_{G,Z}(g,z)}{f_{G}(g)}$$

(56)

or equivalently,
H&J argued that for a randomly selected small positive value of \( \theta \), the non-Granger cause condition shown in Eq. (56) implies the next ratios of joint probabilities:

\[
\frac{C_{E,G,Z}(\theta)}{C_{E,G}(\theta)} = \frac{C_{G,Z}(\theta)}{C_{G}(\theta)} \quad (58)
\]

or,

\[
\frac{C_{E,G,Z}(\theta)}{C_{G}(\theta)} = \frac{C_{G,Z}(\theta)}{C_{G}(\theta)} \quad \frac{C_{E,G}(\theta)}{C_{G}(\theta)} \quad (59)
\]

where, \( C_{w}(\theta) \), with \( W \) any arbitrary multivariate vector taking on values in \( \mathbb{R}^{dw} \), denotes the probability of identifying two independent realizations of the \( W \) vector within a distance which is smaller than or equal to \( \theta \). The above illustrated ratios of the \( C_{w}(\theta) \) correlations integrals are in fact measures of divergence between the two sides of the (56) equality. The general formula for the \( C_{w}(\theta) \) correlation integral is given as follows:

\[
C_{w}(\theta) = P\left[ \|W_{1} - W_{2}\| \leq \theta \right], W_{1}, W_{2}, \text{indep. } \sim W
\]

\[= \iint I\left(\|s_{1} - s_{2}\| \leq \theta\right) f_{s_{1}}(s_{1}) ds_{1} ds_{2} \quad (60)\]

where, \( P[\bullet] \) denoted the probability function, \( \|\bullet\| \) is the maximum norm which for the \( n \)-dimensional vector \( W = \{W_{1}, W_{2}, ..., W_{N}\}^{T} \) is defined as \( \|W\| = \sup_{i=1}^{N} |W_{i}| \), \( I\left(\|s_{1} - s_{2}\| \leq \theta\right) \) is, as previously, the indicator function which takes on the value of 1, if \( \|s_{1} - s_{2}\| \leq \theta \) and 0 otherwise (Dergiades et al., 2011).

To assess statistically the validity of the non-causality condition in Eq. (58) H&J utilized sample estimators for the approximation of the correlations integrals presented in Eq. (61). These estimators have the following form:

\[
\hat{C}_{W,A}(\theta) = \frac{2}{n(n-1)} \sum_{i<j} \sum I_{ij}^{W} \quad (61)
\]
Based on the above estimator, the two ratios of correlation integrals presented in Eq. (59) can be substituted by their respective sample estimators adjusting Eq. (61) accordingly. Subsequently, for given values of $\kappa$, $l_e$, $l_g$ and $\theta$, the ratio difference of the correlation integrals estimators $T$, is proven by H&J that follows the normal distribution (Dergiades et al., 2011).

$$T = \left[ \frac{\hat{C}_{E,G,Z}(\theta, n)}{\hat{C}_{E,G}(\theta, n)} - \frac{\hat{C}_{G,Z}(\theta, n)}{\hat{C}_{G}(\theta, n)} \right] \sim N \left( 0, \frac{1}{\sqrt{n}} \sigma^2(\kappa, l_e, l_g, \theta) \right)$$  \hfill (62)

3.10.2 Diks and Panchenko modification test

Since the H&J test over-rejects, in particular situations, the null hypothesis the Diks and Panchenko (2006) test [hereafter, D&P] make an effort to remedy this shortcoming by introducing a modified Statistic. D&P argued that this observed over-rejection of the null hypothesis results from the aforementioned assumption that Eq. (56) implies Eq. (58). Apparently, the remedy that D&P proposed lead to a restated null hypothesis as follows:

$$q \equiv E \left[ f_{E,G,Z}(E,G,Z) f_G(G) - f_{E,G}(E,G) f_{G,Z}(G,Z) \right] = 0$$  \hfill (63)

while the propose estimator for $q$ is:

$$T_n(\theta_n) = \frac{(2\theta)^{-dE-2dG-2dZ}}{n(n-1)(n-2)} \sum \left[ \sum_{k,k \neq j} \sum_{j \neq i} (I^E_{ik} I^G_{ij} - I^E_{ik} I^{GZ}_{ij}) \right]$$  \hfill (64)

where $I^X_y = I(\|X_i - X_j\| \leq \theta)$, with $I(\bullet)$ being the indicator function and $\theta_n$ the bandwidth which depends on the sample size. The vector $X$ is defined as previously. Thus, if the local density estimator of the vector $X$ at $X_i$ is denoted as $\hat{f}_x(x_i)$, that is:

$$\hat{f}_x(x_i) = (2\theta)^{-d} (n-1)^{-1} \sum_{j \neq i} I^X_y$$  \hfill (65)

At this point, the $T_n(\theta_n)$ Statistic can be expressed in the form that follows:

$$T_n(\theta_n) = \frac{(n-1)}{n(n-2)} \sum_i \left( \hat{f}_{E,G,Z}(E_i,G_i,Z_i) \hat{f}_G(G_i) - \hat{f}_{E,G}(E_i,G_i) \hat{f}_{G,Z}(G_i,Z_i) \right)$$  \hfill (66)
D&P presented that if $\theta_n = Cn^{-\beta}$ with $\left\{ \begin{array}{l} C > 0, \frac{1}{4} < \beta < \frac{1}{3} \end{array} \right. \right.$, then the distribution of the $T_n(\theta_n)$ Statistic converts to the standard normal:

$$\sqrt{n} \left( \frac{T_n(\theta_n) - q}{S_n} \right) \overset{D}{\rightarrow} N(0,1) \quad (67)$$

Where $S_n$ is the asymptotic variance estimator of $T_n(\bullet)$. To this end, via the implementation of the Statistic illustrated in Eq. (67), the risk of over-rejecting the null hypothesis of no causality is reduced, and consequently, the significant drawback of the H&J non-linear hypothesis testing procedure is taken care of (Dergiades et al., 2011).

4. Empirical Application

4.1 Unit root test

Unit root and stationarity test are implemented in the study in order to shed light on the exact order of integration for the time-series under consideration. More specifically, the Augmented Dickey-Fuller (ADF) test (1979), the Generalized Least Squares de-trending Dickey-Fuller (GLS-DF) test and the Phillips and Perron (PP) test (1988) are applied, all of them, with and without a trend.

Additionally to the aforementioned unit root tests, the Kwiatkowski-Phillips-Schmidt-Shin (1992) [KPSS], which is a stationarity test, is implemented. This is a test that has the null hypothesis being stationarity, in contrast with the other three tests, while it is employed in order to verify the results of the unit root tests. As a whole, all these particular tests are used to detect whether the variables are stationary or not while they are examined in level as well as in their first differences to be able to overcome controversies that may surround individual tests.

The results of the first three tests are depicted in Table 2 below. What is obvious, is that the variables are integrated of order one, provided that we fail to reject the null hypothesis in levels in most of the cases (except for energy consumption and GDP, in trend, for the ADF as well as the GLS-DF test). Conversely, when these tests are applied not in the levels but in the
first differences of the time series, we reject the null hypotheses. In other words, the three variables are stationary in their first differences.

Table 2: ADF, GLS-DF and PP unit root tests

<table>
<thead>
<tr>
<th>PANEL A-ADF Unit Root Test</th>
<th>Level</th>
<th>First Difference</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No-trend</td>
<td>Trend</td>
<td>No-trend</td>
</tr>
<tr>
<td>CO2</td>
<td>0.30(1)</td>
<td>-2.12(1)</td>
<td>-4.32(0)***</td>
</tr>
<tr>
<td>EC</td>
<td>-0.79(1)</td>
<td>-3.54(1)*</td>
<td>-3.96(0)***</td>
</tr>
<tr>
<td>GDP</td>
<td>-1.75(0)</td>
<td>-4.40(1)***</td>
<td>-5.04(0)***</td>
</tr>
</tbody>
</table>

Panel B-GLS-DF Unit Root Test

<table>
<thead>
<tr>
<th>Variable</th>
<th>LM-Statistic</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CO2</td>
<td>0.75***</td>
<td></td>
</tr>
<tr>
<td>EC</td>
<td>0.77***</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>0.78***</td>
<td></td>
</tr>
</tbody>
</table>

Panel C-PP Unit Root Test

Notes: The selected lag-length is represented by \(k\). For the ADF as well as for the GLS-DF test, the Schwarz information criterion was applied so as to select the lag-length with \(k_{\text{min}}=0\) and \(k_{\text{max}}=9\). In order to determine the maximum lag-length \(k_{\text{max}}\), the Schwert’s principle (Schwert, 1989), that is, \(k_{\text{max}}=12(n/100)^{0.25}\), with \(n\) to be the sample size. Eventually, *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% level of significance, respectively (Dergiades et al., 2011).

Now, the results of the stationarity KPSS test are depicted in Table 3. What must not be forgotten in this test is that the null hypothesis represents stationarity, the opposite from the ADF, GLS-DF and PP unit root tests. Apparently, the order of integration is the same as in the previous case of the unit root tests. Hence, all the investigated time series can be treated as I(1) variables.

Table 3: KPSS stationarity test

<table>
<thead>
<tr>
<th>PANEL C-PP Unit Root Test</th>
<th>Level</th>
<th>First Difference</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No-trend</td>
<td>Trend</td>
<td>No-trend</td>
</tr>
<tr>
<td>Variable</td>
<td>LM-Statistic</td>
<td>LM-Statistic</td>
<td>LM-Statistic</td>
</tr>
<tr>
<td>CO2</td>
<td>0.75***</td>
<td>0.10</td>
<td>0.12</td>
</tr>
<tr>
<td>EC</td>
<td>0.77***</td>
<td>0.08</td>
<td>0.12</td>
</tr>
<tr>
<td>GDP</td>
<td>0.78***</td>
<td>0.21**</td>
<td>0.38*</td>
</tr>
</tbody>
</table>

Notes: KPSS stands for the Kwiatkowski et al. (1992) stationarity test. The bandwidth for the KPSS test was chosen according to the Newey-West selection procedure, whereas the Bartlett kernel is the spectral estimation method that is used. Finally, *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% level of significance, respectively.
4.2 Unit root tests with breaks

In addition to the abovementioned unit root tests, to eliminate the possibility of false identification of the integration order we test for the existence of unit roots in the time series allowing the presence of one structural break. The unit root tests undertaken for this purpose is the Zivot Andrews (1992) [ZA] and Perron (1989) tests with one structural break. With regard to the null hypothesis, the ZA test undertakes the presence of one structural break whereas the alternative hypothesis suggests stationarity around a structural break. The results of the ZA as well as Perron’s tests are divided into three specifications according to i) break in intercept (Model A), ii) break in trend (Model B) and iii) break in intercept and trend (Model C). The results obtained, specify that the ZA for all models failed to reject the null hypothesis of a unit root, at all the conventional levels of significance.

Table 4: ZA unit root test (with one structural break)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$t$-Stat. ($k$) break</td>
<td>$t$-Stat. ($k$) break</td>
<td>$t$-Stat. ($k$) break</td>
</tr>
<tr>
<td>CO2</td>
<td>-4.25(3)2003</td>
<td>-5.03(3)2003</td>
<td>-5.11(3)1998</td>
</tr>
<tr>
<td>EC</td>
<td>-4.58(3)1996</td>
<td>-4.12(3)2002</td>
<td>-4.80(3)1997</td>
</tr>
<tr>
<td>GDP</td>
<td>-4.79(1)1987</td>
<td>-4.64(1)1978</td>
<td>-5.12(1)1988</td>
</tr>
</tbody>
</table>

Notes: The critical values at the 1%, 5% and 10% level of significance for model A are -5.34, -4.93 and -4.58, respectively. For model B, the critical values for the same significant levels are -4.8, -4.42 and -4.11, respectively. Lastly, the critical values for model C, for the same levels of significance, are -5.57, -5.08 and -4.82, respectively. The above mentioned critical values as a whole are asymptotic and can be traced in Zivot and Andrews (1992). Finally, $k$ represents the selected lag-length, based on the Akaike Information Criterion, which is followed by the chosen break date.

Concerning Perron’s test, we have the same procedure followed as well as the same separation of the three specifications as in the ZA test. Hence, what is identified once more is that Perron’s test for all the models fails to reject the null hypothesis of a unit root, at all the significant levels.
Table 5: Perron unit root test (with one structural break)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model A</th>
<th></th>
<th>Model B</th>
<th></th>
<th>Model C</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t-Stat. (k) break</td>
<td></td>
<td>t-Stat. (k) break</td>
<td></td>
<td>t-Stat. (k) break</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CO₂</td>
<td>-4.20(3)2002</td>
<td></td>
<td>-5.65(3)2003</td>
<td></td>
<td>-5.14(3)1998</td>
<td></td>
</tr>
<tr>
<td>EC</td>
<td>-4.59(3)1996</td>
<td></td>
<td>-3.55(3)2004</td>
<td></td>
<td>-4.81(3)1996</td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>-4.82(1)1987</td>
<td></td>
<td>-4.78(1)1978</td>
<td></td>
<td>-5.03(1)1987</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The critical values at the 1%, 5% and 10% level of significance for model A are -5.92, -5.23 and -4.92, respectively. For model B, the critical values for the same significant levels are -5.45, -4.83 and -4.48, respectively. Finally, the critical values for model C, for the same levels of significance, are -6.32, -5.59 and -5.29, respectively. The k represents the selected lag-length, based on the Akaike Information Criterion, which is followed by the chosen break date.

4.3 The non-linear unit root test of Kapetanios

An additional and supplementary to the aforementioned unit root tests is the one that proposed by Kapetanios, Shin and Snell (2008) [KSS] and employed by Zhou et al.(2008). It is a non-linear unit root test and presents a new technique regarding the null hypothesis of a unit root against an alternative one of non-linear stationary smooth transition. In response to this, Table 6 illustrates the results obtained by the KSS unit root test.

Table 6: The KSS non-linear unit root test

<table>
<thead>
<tr>
<th>Sample</th>
<th>1971-2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A-Level</td>
<td></td>
</tr>
<tr>
<td>Variable</td>
<td>Case 1 ($t_{NL}$)</td>
</tr>
<tr>
<td>CO₂</td>
<td>2.616</td>
</tr>
<tr>
<td>EC</td>
<td>2.997</td>
</tr>
<tr>
<td>GDP</td>
<td>5.450</td>
</tr>
<tr>
<td>Panel B-First Difference</td>
<td></td>
</tr>
<tr>
<td>CO₂</td>
<td>-1.493</td>
</tr>
<tr>
<td>EC</td>
<td>0.320</td>
</tr>
<tr>
<td>GDP</td>
<td>-0.807</td>
</tr>
</tbody>
</table>

Notes: $t_{NL}$, $t_{NL1}$ and $t_{NL2}$ refer to the model with the raw data, the de-meaned data and the de-trended data, respectively.
4.4 Cointegration tests

Since the basic idea that exists behind cointegration is to test whether a linear combination of two individually non-stationary time series is stationary by itself, the Johansen (1990) and the Engle-Granger (1987) cointegration tests are applied to examine the existence of this long-run relationship among the variables. Table 7 presents the results of the Johansen (1990) cointegration test as determined by the maximum eigenvalue and the trace procedure. To this end, what becomes evident in the results is that the null hypothesis of zero cointegrating relationships is not rejected at any conventional level of significance.

Table 7: The Johansen cointegration test

<table>
<thead>
<tr>
<th>Null</th>
<th>Alternative</th>
<th>Eigen value</th>
<th>Trace Stat.</th>
<th>5% critical</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>r = 0</td>
<td>r = 1</td>
<td>0.228</td>
<td>17.677</td>
<td>29.797</td>
<td>0.590</td>
</tr>
<tr>
<td>r ≤ 1</td>
<td>r = 2</td>
<td>0.196</td>
<td>8.346</td>
<td>15.495</td>
<td>0.429</td>
</tr>
<tr>
<td>r ≤ 2</td>
<td>r = 3</td>
<td>0.013</td>
<td>0.483</td>
<td>3.841</td>
<td>0.487</td>
</tr>
</tbody>
</table>

Notes: The analysis is based on a VAR with constant term and one lag for the endogenous variables. The VAR lag interval in the first differences was calculated based on the Akaike Information Criterion to be equal one.

Additionally, Table 8 presents the results of the Engle and Granger (1987) cointegration approach. Once again, the outcomes reveal that the null hypothesis is not rejected, and hence the time series are not cointegrated.

Table 8: The Engle and Granger cointegration test

<table>
<thead>
<tr>
<th>Dependent</th>
<th>tau-statistic</th>
<th>p-value</th>
<th>z-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO₂</td>
<td>-1.981</td>
<td>0.745</td>
<td>-7.789</td>
<td>0.712</td>
</tr>
<tr>
<td>EC</td>
<td>-2.877</td>
<td>0.325</td>
<td>-11.159</td>
<td>0.464</td>
</tr>
<tr>
<td>GDP</td>
<td>-2.565</td>
<td>0.496</td>
<td>-9.483</td>
<td>0.586</td>
</tr>
</tbody>
</table>

Notes: The lag specification is based on the Schwarz Information Criterion and the maximum lags are 9.

The ARDL bounds testing approach to cointegration developed by Pesaran et al. (2001) contains several advantages in comparison to other cointegration procedures. The ARDL bounds testing approach is complementary to the Johansen’s maximum likelihood test, and it can be estimated by OLS. Despite the fact that the Johansen (1990) method has disadvantages concerning the sample size and the different lag length, the ARDL approach does not. Furthermore, it can be applied regardless of the order of integration that the time series have.
It is preferred to other conventional tests since the Monte Carlo evidence displays some important advantages over the tests of Johansen (1990) and Engle-Granger (1987). The results of the test are illustrated on Table 9.

Table 9: The ARDL bounds testing approach

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>F-Statistics</th>
<th>Alternative lag lengths</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>$F(CO_2</td>
<td>EC, GDP)$</td>
<td>2.075</td>
</tr>
<tr>
<td>$F(EC</td>
<td>CO_2, GDP)$</td>
<td>2.441</td>
</tr>
<tr>
<td>$F(GDP</td>
<td>CO_2, EC)$</td>
<td>1.981</td>
</tr>
</tbody>
</table>

*Notes: *, **, *** denote the presence of co-integration at 10%, 5% and 1% level of significance, respectively. For $n=35$ and $k=3$ the pairs of critical values are 5.198-6.845, 3.615-4.913 and 2.958-4.100 for 0.01, 0.05 and 0.1 respectively. The critical values were obtained from Narayan (2005), pg. 1988, case III.

4.5 The BDS test

In an attempt to identify non-linear causality, the non-linear dependence test proposed by Brock et al. (1996) is implemented, the widely known as BDS test. Since the BDS test can be applied to the residuals derived from the de-linearization of the series, the validity of the i.i.d. (independent and identically distributed) assumption on these data is examined through this particular test. The de-linearization of the series occurs within a multivariate framework. The testing results corresponding to the residuals (for the GDP, CO$_2$ and energy consumption equation) obtained from unrestricted VAR specifications are demonstrated on the following Tables.

Table 10: The BDS test (CO$_2$)

<table>
<thead>
<tr>
<th>Dimension</th>
<th>BDS-Stat.</th>
<th>Std. error</th>
<th>Z-Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.019**</td>
<td>0.009</td>
<td>2.184</td>
<td>0.029</td>
</tr>
<tr>
<td>3</td>
<td>0.042***</td>
<td>0.014</td>
<td>2.942</td>
<td>0.003</td>
</tr>
<tr>
<td>4</td>
<td>0.049***</td>
<td>0.018</td>
<td>2.803</td>
<td>0.005</td>
</tr>
<tr>
<td>5</td>
<td>0.065***</td>
<td>0.019</td>
<td>3.469</td>
<td>0.001</td>
</tr>
<tr>
<td>6</td>
<td>0.059***</td>
<td>0.018</td>
<td>3.186</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*Notes: *, **, *** denote rejection of the i.i.d. assumption at 10%, 5% and 1% level of significance, respectively. The VAR lag-order is equal to one while was selected based on the Akaike Information Criterion.
Table 11: The BDS test (EC)

<table>
<thead>
<tr>
<th>Dimension</th>
<th>BDS-Stat.</th>
<th>Std. error</th>
<th>Z-Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.023*</td>
<td>0.013</td>
<td>1.823</td>
<td>0.068</td>
</tr>
<tr>
<td>3</td>
<td>0.046**</td>
<td>0.021</td>
<td>2.267</td>
<td>0.023</td>
</tr>
<tr>
<td>4</td>
<td>0.059***</td>
<td>0.025</td>
<td>2.366</td>
<td>0.018</td>
</tr>
<tr>
<td>5</td>
<td>0.081***</td>
<td>0.027</td>
<td>3.061</td>
<td>0.002</td>
</tr>
<tr>
<td>6</td>
<td>0.088***</td>
<td>0.026</td>
<td>3.362</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Notes: *, **, *** denote rejection of the i.i.d. assumption at 10%, 5% and 1% level of significance, respectively. The VAR lag-order is equal to one while was selected based on the Akaike Information Criterion.

Table 12: The BDS test (GDP)

<table>
<thead>
<tr>
<th>Dimension</th>
<th>BDS-Stat.</th>
<th>Std. error</th>
<th>Z-Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.035***</td>
<td>0.012</td>
<td>2.905</td>
<td>0.004</td>
</tr>
<tr>
<td>3</td>
<td>0.079***</td>
<td>0.019</td>
<td>4.024</td>
<td>0.000</td>
</tr>
<tr>
<td>4</td>
<td>0.098***</td>
<td>0.024</td>
<td>4.082</td>
<td>0.000</td>
</tr>
<tr>
<td>5</td>
<td>0.120***</td>
<td>0.026</td>
<td>4.468</td>
<td>0.000</td>
</tr>
<tr>
<td>6</td>
<td>0.130***</td>
<td>0.025</td>
<td>5.137</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: *, **, *** denote rejection of the i.i.d. assumption at 10%, 5% and 1% level of significance, respectively. The VAR lag-order is equal to one while was selected based on the Akaike Information Criterion.

4.6 Parametric causality tests

The Standard Granger causality test is valid when variables have no cointegrating relationship. It is used in order to investigate the existence of a linear causality running among the three variables under examination, for instance, from economic growth to CO₂ emissions, and it is of great importance to examine the F-Statistic that is obtaining after testing the joint significance of the lagged GDP values to explain the current level of CO₂ emissions. In this dissertation, there are three pairs of variables that are suited for applying this test, namely EC/GDP, CO₂/GDP and CO₂/EC. The following Table illustrates the results.
Table 13: The Standard Granger causality test

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>VAR lag</th>
<th>F-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC does not Granger cause GDP</td>
<td>1.000</td>
<td>2.071</td>
<td>0.159</td>
</tr>
<tr>
<td>GDP does not Granger cause EC</td>
<td>1.000</td>
<td>1.762</td>
<td>0.193</td>
</tr>
<tr>
<td>CO₂ does not Granger cause GDP</td>
<td>1.000</td>
<td>0.719</td>
<td>0.402</td>
</tr>
<tr>
<td>GDP does not Granger cause CO₂</td>
<td>1.000</td>
<td>0.177</td>
<td>0.677</td>
</tr>
<tr>
<td>CO₂ does not Granger cause EC</td>
<td>1.000</td>
<td>0.326</td>
<td>0.572</td>
</tr>
<tr>
<td>EC does not Granger cause CO₂</td>
<td>1.000</td>
<td>9.760***</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Notes: The VAR lag order was selected based on the Akaike Information Criterion. The selected lag order is equal to one.

The Toda-Yamamoto (1995) [TY] procedure is another test for the existence of long-run Granger’s causality which, in contrast with others, does not require pre-testing for cointegration. Hence, it enables feedback effects through several lags. What is more, the TY procedure involves an “augmented” VAR in levels; thus, no information is lost due to differencing. Table 14 depicts the results.

Table 14: Granger causality test results based on the TY procedures

<table>
<thead>
<tr>
<th>Models</th>
<th>χ²-statistic</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO₂ - EC</td>
<td>6.713** (0.035)</td>
<td>EC → CO₂</td>
</tr>
<tr>
<td>CO₂ - GDP</td>
<td>6.987** (0.030)</td>
<td>GDP → CO₂</td>
</tr>
<tr>
<td>EC - CO₂</td>
<td>2.609 (0.271)</td>
<td>-</td>
</tr>
<tr>
<td>EC - GDP</td>
<td>5.037* (0.081)</td>
<td>GDP → EC</td>
</tr>
<tr>
<td>GDP - CO₂</td>
<td>1.302 (0.521)</td>
<td>-</td>
</tr>
<tr>
<td>GDP - EC</td>
<td>1.201 (0.548)</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes: *, ** and *** indicate the significance level at 10%, 5% and 1%, respectively. According to the Akaike Information Criterion the optimal lag length is two.

The Hsiao causality method (1979) is a two-step method that combines the Akaike’s Final Prediction Error (FPE) with the Granger causality test through a VECM approach, in order to determine the optimum number of own-lagged and cross-lagged terms as well as the causality direction of two or more variables. Table 15 depicts the results of the test.
<table>
<thead>
<tr>
<th>Variables</th>
<th>FPE</th>
<th>Causality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p = 1$</td>
<td>$p = 2$</td>
</tr>
<tr>
<td>CO$_2$</td>
<td>0.000449*</td>
<td>0.000454</td>
</tr>
<tr>
<td>CO$_2$ - EC</td>
<td>0.000367</td>
<td>0.000360</td>
</tr>
<tr>
<td>CO$_2$ - GDP</td>
<td>0.000473</td>
<td>0.000372</td>
</tr>
<tr>
<td>EC</td>
<td>0.000277</td>
<td>0.000254</td>
</tr>
<tr>
<td>EC - GDP</td>
<td>0.000264</td>
<td>0.000238*</td>
</tr>
<tr>
<td>EC - CO$_2$</td>
<td>0.000278</td>
<td>0.000285</td>
</tr>
<tr>
<td>GDP</td>
<td>0.000240</td>
<td>0.000196*</td>
</tr>
<tr>
<td>GDP - CO$_2$</td>
<td>0.000196</td>
<td>0.000191*</td>
</tr>
<tr>
<td>GDP - EC</td>
<td>0.000190</td>
<td>0.000186*</td>
</tr>
</tbody>
</table>

Notes: CO$_2$, EC and GDP stand for carbon dioxide emissions, energy consumption and Gross Domestic Product, respectively. The * denotes the optimal lag length in each case.

4.7 Non-parametric causality tests

To the best of our knowledge, the analysis does not end to the application of Granger, TY, and Hsiao causality tests, but continues with the implementation of two additional non-linear causality tests. For this purpose, there are three sequential steps for testing the Hiemstra and Jones (1994) [H&J] and Diks and Panchenko (2006) [D&P] procedures. In the first one, both the tests are implemented directly into the growth rates of the time series, whereas in the second step, both tests are reapplied on the de-linearized series through a multivariate VAR specification. This step is important to make sure that any detected causality is non-linear in nature. Lastly, the third step is to use a GARCH-BEKK filter for our multivariate framework. The results of the first step are displayed in the Table 16, whereas Table 17 illustrates the results of the second step. Last but not least, the third step’s results are presented in Table 18. In order to implement the test a 1.5 bandwidth has been selected.
Table 16: Non-parametric causality tests (Growth Rates)

<table>
<thead>
<tr>
<th></th>
<th>H.J.(p)-value</th>
<th>D.P.(p)-value</th>
<th>H.J.(p)-value</th>
<th>D.P.(p)-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(l_x = l_y)</td>
<td>(l_x \rightarrow l_y)</td>
<td>(l_x \rightarrow l_y)</td>
<td>(l_x \rightarrow l_y)</td>
<td>(l_x \rightarrow l_y)</td>
</tr>
<tr>
<td></td>
<td>(H.J.)</td>
<td>(D.P.)</td>
<td>(H.J.)</td>
<td>(D.P.)</td>
</tr>
<tr>
<td>Without filtering (step one)-non-linear (growth rates)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(CO_2 \rightarrow EC)</td>
<td>(EC \rightarrow CO_2)</td>
<td>(EC \rightarrow CO_2)</td>
<td>(EC \rightarrow CO_2)</td>
<td>(EC \rightarrow CO_2)</td>
</tr>
<tr>
<td>1</td>
<td>1.113 (0.133)</td>
<td>0.624 (0.266)</td>
<td>0.865 (0.193)</td>
<td>1.044 (0.148)</td>
</tr>
<tr>
<td>2</td>
<td>1.086 (0.138)</td>
<td>0.912 (0.181)</td>
<td>1.180 (0.119)</td>
<td>1.173 (0.120)</td>
</tr>
<tr>
<td>3</td>
<td>1.168 (0.121)</td>
<td>0.794 (0.214)</td>
<td>1.908** (0.028)</td>
<td>1.341* (0.089)</td>
</tr>
<tr>
<td>4</td>
<td>0.997 (0.159)</td>
<td>0.867 (0.193)</td>
<td>0.145 (0.442)</td>
<td>0.222 (0.412)</td>
</tr>
<tr>
<td>5</td>
<td>0.911 (0.181)</td>
<td>0.789 (0.215)</td>
<td>0.024 (0.490)</td>
<td>0.076 (0.469)</td>
</tr>
<tr>
<td>6</td>
<td>0.354 (0.362)</td>
<td>0.156 (0.437)</td>
<td>-0.299 (0.617)</td>
<td>-0.190 (0.575)</td>
</tr>
<tr>
<td>7</td>
<td>0.461 (0.322)</td>
<td>0.464 (0.321)</td>
<td>0.263 (0.396)</td>
<td>0.069 (0.473)</td>
</tr>
<tr>
<td>8</td>
<td>0.334 (0.369)</td>
<td>0.274 (0.392)</td>
<td>0.069 (0.472)</td>
<td>0.348 (0.364)</td>
</tr>
<tr>
<td>(CO_2 \rightarrow GDP)</td>
<td>(GDP \rightarrow CO_2)</td>
<td>(GDP \rightarrow CO_2)</td>
<td>(GDP \rightarrow CO_2)</td>
<td>(GDP \rightarrow CO_2)</td>
</tr>
<tr>
<td>1</td>
<td>0.586 (0.279)</td>
<td>0.461 (0.322)</td>
<td>1.933** (0.027)</td>
<td>1.772** (0.038)</td>
</tr>
<tr>
<td>2</td>
<td>1.118 (0.132)</td>
<td>1.038 (0.149)</td>
<td>3.041*** (0.001)</td>
<td>1.820** (0.034)</td>
</tr>
<tr>
<td>3</td>
<td>0.527 (0.299)</td>
<td>0.259 (0.397)</td>
<td>1.607** (0.054)</td>
<td>1.118 (0.132)</td>
</tr>
<tr>
<td>4</td>
<td>0.592 (0.277)</td>
<td>0.459 (0.323)</td>
<td>0.894 (0.186)</td>
<td>0.637 (0.262)</td>
</tr>
<tr>
<td>5</td>
<td>0.804 (0.211)</td>
<td>0.546 (0.292)</td>
<td>0.252 (0.401)</td>
<td>0.257 (0.398)</td>
</tr>
<tr>
<td>6</td>
<td>0.306 (0.379)</td>
<td>-0.151 (0.559)</td>
<td>0.264 (0.396)</td>
<td>0.447 (0.327)</td>
</tr>
<tr>
<td>7</td>
<td>1.626** (0.051)</td>
<td>0.936 (0.175)</td>
<td>0.015 (0.494)</td>
<td>0.234 (0.407)</td>
</tr>
<tr>
<td>8</td>
<td>2.042** (0.021)</td>
<td>1.015 (0.155)</td>
<td>-0.306 (0.620)</td>
<td>0.069 (0.472)</td>
</tr>
<tr>
<td>(EC \rightarrow GDP)</td>
<td>(GDP \rightarrow EC)</td>
<td>(GDP \rightarrow EC)</td>
<td>(GDP \rightarrow EC)</td>
<td>(GDP \rightarrow EC)</td>
</tr>
<tr>
<td>1</td>
<td>1.854** (0.032)</td>
<td>2.029** (0.021)</td>
<td>0.978 (0.164)</td>
<td>0.576 (0.282)</td>
</tr>
<tr>
<td>2</td>
<td>1.432* (0.076)</td>
<td>1.696** (0.045)</td>
<td>1.309* (0.095)</td>
<td>1.134 (0.128)</td>
</tr>
<tr>
<td>3</td>
<td>1.489* (0.068)</td>
<td>1.372* (0.085)</td>
<td>0.287 (0.387)</td>
<td>-0.164 (0.565)</td>
</tr>
<tr>
<td>4</td>
<td>1.198 (0.116)</td>
<td>1.240 (0.107)</td>
<td>1.124 (0.131)</td>
<td>0.498 (0.309)</td>
</tr>
<tr>
<td>5</td>
<td>0.208 (0.417)</td>
<td>0.302 (0.381)</td>
<td>0.121 (0.452)</td>
<td>-0.350 (0.637)</td>
</tr>
<tr>
<td>6</td>
<td>-0.146 (0.558)</td>
<td>-0.295 (0.616)</td>
<td>0.171 (0.432)</td>
<td>0.045 (0.482)</td>
</tr>
<tr>
<td>7</td>
<td>-0.033 (0.513)</td>
<td>-0.428 (0.666)</td>
<td>-0.016 (0.506)</td>
<td>0.219 (0.413)</td>
</tr>
<tr>
<td>8</td>
<td>0.773 (0.219)</td>
<td>0.044 (0.483)</td>
<td>-0.512 (0.696)</td>
<td>-0.562 (0.713)</td>
</tr>
</tbody>
</table>

Notes: *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% level of significance, respectively. The selected VAR lag-order, based on the Akaike Information Criterion, is equal to 1. The values in parentheses are \(p\)-values.
Table 17: Non-parametric causality tests (VAR residuals)

\[ l_x = l_y \]

<table>
<thead>
<tr>
<th></th>
<th>H.J.(p-value)</th>
<th>D.P.(p-value)</th>
<th>H.J.(p-value)</th>
<th>D.P.(p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>With VAR filtering (step two)-non-linear (residuals)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>CO(_2) → EC</td>
<td></td>
<td>EC → CO(_2)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.218 (0.586)</td>
<td>-0.628 (0.607)</td>
<td>-0.213 (0.584)</td>
<td>-0.273 (0.607)</td>
</tr>
<tr>
<td>2</td>
<td>-0.552 (0.709)</td>
<td>-0.584 (0.761)</td>
<td>-0.656 (0.744)</td>
<td>-0.708 (0.761)</td>
</tr>
<tr>
<td>3</td>
<td>0.406 (0.342)</td>
<td>0.139 (0.531)</td>
<td>0.079 (0.469)</td>
<td>-0.078 (0.531)</td>
</tr>
<tr>
<td>4</td>
<td>0.465 (0.321)</td>
<td>0.103 (0.584)</td>
<td>0.152 (0.439)</td>
<td>-0.213 (0.584)</td>
</tr>
<tr>
<td>5</td>
<td>0.016 (0.493)</td>
<td>-0.408 (0.331)</td>
<td>0.022 (0.491)</td>
<td>0.436 (0.331)</td>
</tr>
<tr>
<td>6</td>
<td>0.241 (0.405)</td>
<td>-0.348 (0.448)</td>
<td>-0.955 (0.830)</td>
<td>0.131 (0.448)</td>
</tr>
<tr>
<td>7</td>
<td>-0.089 (0.536)</td>
<td>-0.347 (0.826)</td>
<td>-0.089 (0.923)</td>
<td>-0.939 (0.826)</td>
</tr>
<tr>
<td>8</td>
<td>-0.098 (0.539)</td>
<td>-0.450 (0.404)</td>
<td>-0.098 (0.529)</td>
<td>0.242 (0.404)</td>
</tr>
<tr>
<td></td>
<td>CO(_2) → GDP</td>
<td>GDP → CO(_2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1.139 (0.873)</td>
<td>-1.479 (0.930)</td>
<td>1.449 (0.236)</td>
<td>1.507* (0.065)</td>
</tr>
<tr>
<td>2</td>
<td>-0.987 (0.838)</td>
<td>-1.482 (0.931)</td>
<td>1.077 (0.258)</td>
<td>0.929 (0.176)</td>
</tr>
<tr>
<td>3</td>
<td>-1.326 (0.907)</td>
<td>-1.604 (0.946)</td>
<td>0.148 (0.379)</td>
<td>-0.198 (0.578)</td>
</tr>
<tr>
<td>4</td>
<td>-0.991 (0.839)</td>
<td>-1.464 (0.928)</td>
<td>0.475 (0.702)</td>
<td>-0.107 (0.543)</td>
</tr>
<tr>
<td>5</td>
<td>-0.685 (0.753)</td>
<td>-1.119 (0.868)</td>
<td>0.662 (0.900)</td>
<td>-0.162 (0.435)</td>
</tr>
<tr>
<td>6</td>
<td>-0.120 (0.548)</td>
<td>-0.483 (0.685)</td>
<td>-0.665 (0.818)</td>
<td>-0.728 (0.767)</td>
</tr>
<tr>
<td>7</td>
<td>0.074 (0.470)</td>
<td>-0.393 (0.653)</td>
<td>-0.636 (0.672)</td>
<td>-0.407 (0.658)</td>
</tr>
<tr>
<td>8</td>
<td>0.184 (0.427)</td>
<td>-0.078 (0.531)</td>
<td>-0.826 (0.748)</td>
<td>-0.434 (0.668)</td>
</tr>
<tr>
<td></td>
<td>EC → GDP</td>
<td>GDP → EC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-1.213 (0.887)</td>
<td>-0.921 (0.821)</td>
<td>0.718 (0.236)</td>
<td>0.671 (0.251)</td>
</tr>
<tr>
<td>2</td>
<td>-0.179 (0.571)</td>
<td>-0.199 (0.579)</td>
<td>0.651 (0.257)</td>
<td>0.751 (0.226)</td>
</tr>
<tr>
<td>3</td>
<td>-0.217 (0.586)</td>
<td>-0.312 (0.622)</td>
<td>0.306 (0.379)</td>
<td>0.096 (0.462)</td>
</tr>
<tr>
<td>4</td>
<td>-0.123 (0.549)</td>
<td>-0.045 (0.518)</td>
<td>-0.529 (0.702)</td>
<td>-0.705 (0.759)</td>
</tr>
<tr>
<td>5</td>
<td>-0.655 (0.744)</td>
<td>-0.726 (0.766)</td>
<td>-1.282 (0.900)</td>
<td>-1.323 (0.907)</td>
</tr>
<tr>
<td>6</td>
<td>-0.151 (0.560)</td>
<td>-0.283 (0.612)</td>
<td>-0.907 (0.818)</td>
<td>-0.981 (0.837)</td>
</tr>
<tr>
<td>7</td>
<td>0.072 (0.471)</td>
<td>0.452 (0.326)</td>
<td>-0.446 (0.672)</td>
<td>-0.823 (0.795)</td>
</tr>
<tr>
<td>8</td>
<td>0.551 (0.291)</td>
<td>0.946 (0.172)</td>
<td>-0.669 (0.748)</td>
<td>-0.810 (0.791)</td>
</tr>
</tbody>
</table>

Notes: *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% level of significance, respectively. The selected VAR lag-order, based on the Akaike Information Criterion, is equal to 1. The values in parentheses are p-values.
Table 18: Non-parametric causality tests (GARCH residuals)

<table>
<thead>
<tr>
<th></th>
<th>H.J.(p-value)</th>
<th>D.P.(p-value)</th>
<th>H.J.(p-value)</th>
<th>D.P.(p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$lx = ly$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With GARCH-BEKK filtering (step three)-non-linear (GARCH residuals)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>CO₂ → EC</th>
<th></th>
<th>EC → CO₂</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.952 (0.170)</td>
<td>0.999 (0.159)</td>
<td>-0.378 (0.647)</td>
<td>-0.353 (0.638)</td>
</tr>
<tr>
<td>2</td>
<td>0.841 (0.200)</td>
<td>0.932 (0.175)</td>
<td>0.620 (0.267)</td>
<td>0.413 (0.339)</td>
</tr>
<tr>
<td>3</td>
<td>1.089 (0.138)</td>
<td>1.088 (0.138)</td>
<td>0.282 (0.389)</td>
<td>0.266 (0.395)</td>
</tr>
<tr>
<td>4</td>
<td>1.898** (0.029)</td>
<td>1.948** (0.026)</td>
<td>0.469 (0.319)</td>
<td>0.543 (0.293)</td>
</tr>
<tr>
<td>5</td>
<td>2.249** (0.012)</td>
<td>1.883** (0.029)</td>
<td>1.515* (0.064)</td>
<td>1.462* (0.072)</td>
</tr>
<tr>
<td>6</td>
<td>1.728** (0.042)</td>
<td>1.353* (0.088)</td>
<td>1.296* (0.097)</td>
<td>1.179 (0.119)</td>
</tr>
<tr>
<td>7</td>
<td>1.777** (0.038)</td>
<td>1.348* (0.089)</td>
<td>1.019 (0.154)</td>
<td>1.068 (0.143)</td>
</tr>
<tr>
<td>8</td>
<td>1.313* (0.094)</td>
<td>1.243 (0.107)</td>
<td>0.971 (0.166)</td>
<td>0.653 (0.257)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>CO₂ → GDP</th>
<th></th>
<th>GDP → CO₂</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.931 (0.824)</td>
<td>-0.966 (0.833)</td>
<td>0.557 (0.288)</td>
<td>0.405 (0.343)</td>
</tr>
<tr>
<td>2</td>
<td>1.766** (0.039)</td>
<td>1.512* (0.065)</td>
<td>0.831 (0.203)</td>
<td>0.790 (0.215)</td>
</tr>
<tr>
<td>3</td>
<td>0.519 (0.302)</td>
<td>0.390 (0.348)</td>
<td>0.747 (0.227)</td>
<td>0.289 (0.386)</td>
</tr>
<tr>
<td>4</td>
<td>0.468 (0.319)</td>
<td>0.372 (0.355)</td>
<td>2.022** (0.022)</td>
<td>1.783** (0.037)</td>
</tr>
<tr>
<td>5</td>
<td>0.069 (0.472)</td>
<td>-0.279 (0.609)</td>
<td>1.569* (0.058)</td>
<td>1.080 (0.139)</td>
</tr>
<tr>
<td>6</td>
<td>-0.580 (0.719)</td>
<td>0.189 (0.425)</td>
<td>-0.383 (0.649)</td>
<td>-0.435 (0.668)</td>
</tr>
<tr>
<td>7</td>
<td>0.351 (0.363)</td>
<td>0.252 (0.401)</td>
<td>0.890 (0.187)</td>
<td>0.420 (0.337)</td>
</tr>
<tr>
<td>8</td>
<td>0.441 (0.329)</td>
<td>0.896 (0.185)</td>
<td>1.110 (0.133)</td>
<td>0.579 (0.281)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>EC → GDP</th>
<th></th>
<th>GDP → EC</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.189 (0.425)</td>
<td>0.463 (0.321)</td>
<td>1.065 (0.143)</td>
<td>0.737 (0.231)</td>
</tr>
<tr>
<td>2</td>
<td>-0.543 (0.706)</td>
<td>-0.274 (0.608)</td>
<td>1.503* (0.066)</td>
<td>1.267 (0.103)</td>
</tr>
<tr>
<td>3</td>
<td>0.516 (0.303)</td>
<td>0.178 (0.429)</td>
<td>1.491* (0.068)</td>
<td>0.956 (0.169)</td>
</tr>
<tr>
<td>4</td>
<td>-0.084 (0.534)</td>
<td>-0.404 (0.657)</td>
<td>2.794*** (0.002)</td>
<td>1.931** (0.027)</td>
</tr>
<tr>
<td>5</td>
<td>0.608 (0.271)</td>
<td>-0.000 (0.500)</td>
<td>1.918** (0.027)</td>
<td>1.199 (0.115)</td>
</tr>
<tr>
<td>6</td>
<td>0.802 (0.211)</td>
<td>0.799 (0.212)</td>
<td>1.511* (0.065)</td>
<td>1.300* (0.097)</td>
</tr>
<tr>
<td>7</td>
<td>0.834 (0.202)</td>
<td>0.896 (0.185)</td>
<td>1.497* (0.067)</td>
<td>1.262 (0.103)</td>
</tr>
<tr>
<td>8</td>
<td>0.351 (0.363)</td>
<td>0.252 (0.401)</td>
<td>0.890 (0.187)</td>
<td>0.420 (0.337)</td>
</tr>
</tbody>
</table>

Notes: *, ** and *** denote rejection of the null hypothesis at the 10%, 5% and 1% level of significance, respectively. The selected VAR lag-order, based on the Akaike Information Criterion, is equal to 1. The values in parentheses are p-values.
5. Discussion of the results

5.1 Unit root test results

In an attempt to investigate whether the variables in the study are integrated of order zero or one, a number of unit root tests are implemented. The results of these tests for CO\textsubscript{2} emissions, energy consumption and economic growth are reported in Table 2 (ADF, GLS-DF and PP unit root tests) and Table 3 (KPSS stationarity test). What is obvious from the first three tests, is that the variables are integrated of order one provided that the null hypothesis is failed to be rejected, in levels, in most of the cases. There is an exception for the variables of energy consumption and GDP, for the ADF as well as the GLS-DF test, where the null hypothesis is rejected in trend. Contrariwise, when these tests are applied not in the levels but in the first differences of the time series, we reject the null hypotheses. In other words, the three variables are stationary in their first differences. Moreover, it is clear that the null hypothesis is consistently rejected at the 0.1 level of significance. The same order of integration characterizes the remaining KPSS stationarity test which is the one that verifies the results of the other unit root tests as well as it allows for the robustness of the results derived from the comparison of the outcomes obtained.

Apart from the abovementioned unit root tests, two more (ZA and Perron unit root tests) are conducted to detect if there are unit roots with breaks, or not. This is a way to eliminate false identification of the integration order. The results with the corresponding critical values are presented in Table 4 (ZA unit root test) and Table 5 (Perron unit root test). The series are I(1) when we are unable to reject the null hypothesis. Neither the break in the intercept nor slope, nor both are statistically significant in model A and C for the three variables under investigation since we fail to reject the null hypothesis. Only in model B, for CO\textsubscript{2} emissions, stationarity under one break can be detected. Is the only case where the null hypothesis is rejected at the 0.01 level of significance. The statistical significant break is in 2003 for CO\textsubscript{2} emissions.

There is an additional unit root test that has been implemented in the study, the KSS test, which is a non-linear unit root test. The KSS test modifies the data according to the appropriate case in order to accommodate stochastic procedures with non-zero means and/or linear deterministic trends. Table 6 illustrates the results from this test. According to the asymptotic critical values of $t_{NL}$, in each one of the three cases, it is obvious that the null
hypothesis is consistently failed to be rejected in levels. So, there is non-linearity in the series. The same results are evident in the first differences as well, with some exceptions concerning CO\textsubscript{2} emissions and GDP. With regard to CO\textsubscript{2} emissions, the null hypothesis is rejected in Case 3 ($t_{NL2}$), while for GDP, the null is rejected in Case 2 ($t_{NL1}$) and Case 3 ($t_{NL2}$) and thus, linearity is apparent only for these particular cases.

5.2 Cointegration test results

The basic idea behind the cointegration tests is whether a linear combination of two non-stationary variables is stationary by itself over the sample period. Since the results from the unit root tests reveal that the underlying variables share common integration properties, it is time to proceed with testing the existence of long-run relationship between them. A multivariate model, including the three variables (CO\textsubscript{2} emissions, energy consumption and GDP) has been estimated. Three cointegration tests are implemented to get the results. The outcomes of these tests are illustrated in Table 7 (for Johansen cointegration test), Table 8 (for Engle and Granger cointegration test) and Table 9 (for the ARDL bounds testing approach).

What is evident from the results from the Johansen (1990) cointegration test is that the null hypothesis of zero cointegrating relationships is not rejected at any conventional level of significance. The trace statistic indicates that there is no cointegration at the 0.05 level while the AIC is used to calculate the lag interval in the first differences. The Engle and Granger (1987) cointegration test gives results that reject the null hypothesis as well. Consequently, even for this test there is no cointegration between the variables. The Schwartz criterion is used for this case whereas the maximum lags are nine.

In order to obtain the results from the ARDL bounds testing approach (Table 9) the Wald-test has been accomplished by imposing one, two and three lags. The computed $F$-Statistics are compared with the critical values provided by Narayan (2005) since the sample size of the study is small. In general, there is no presence of cointegration in this test, as well as in the aforementioned (Johansen and Engle and Granger). There is only one exception with regard to the demand function $F$(CO\textsubscript{2}|EC, GDP), where cointegration is evident to 0.05 level of significance. In this case, the $F$-statistic is greater than the critical values at the third lag. Obviously, what is obtained is a conclusion with no evidence of cointegration for any of the tests.
5.3 BDS test results

The BDS test is the non-linear dependence test applied on residuals that assesses the i.i.d. assumption on the de-linearized time-series data. Tables 10, 11 and 12 present the results of the BDS test in the time series of CO₂ emissions, energy consumption and GDP, respectively. What is clearly defined from the three tables is that the i.i.d. (independent and identically distributed) assumption is consistently rejected, irrespectively of the imposed dimension, for different levels of significance. Particularly, on Table 10, the i.i.d. assumption is rejected at the 0.05 significance level for the second dimension while is rejected at the 0.01 level of significance for the remaining dimensions. For Table 11, the i.i.d. assumption is rejected at the 0.1 for the second dimension, at the 0.05 for the next two and at the 0.01 significance level for the remaining two. Finally, on Table 12 for the whole of dimensions, the i.i.d. assumption is rejected at the 0.01 level of significance. Hence, the results apparently reveal that non-linearity exists and the non-linear causality tests are the most appropriate to be implemented.

5.4 Parametric causality tests

In order to investigate the presence of linear causality between the variables under examination we implement three causality tests, namely, the standard Granger causality test, the TY approach and the Hsiao causality method. The standard Granger causality test is obtained from the estimation of an unrestricted VAR model with the variables included to be transformed in their first differences. The existence of a linear causality is detected by observing the $F$-Statistic which is obtained after testing the joint significance of one variable’s lagged values in explaining the current level of the other variable. The results in Table 13 show that there is unidirectional causality running from energy consumption to CO₂ emissions at the 0.05 level of significance ($F=9.760$). Nevertheless, no significant causality is evident to the opposite direction (from CO₂ emissions to energy consumption) concerning the $F$-Statistic ($F=0.326$). This is the only causality detected between the three variables under examination since there is no evidence for other relationships just based on the $F$-Statistics. Thus, the reduction of energy consumption seems to be the most suitable way to reduce CO₂ emissions.

The TY is another procedure to test for long-run Granger causality and does not require any pre-testing for cointegration. Table 14 provides the results of the TY procedure with the optimal lag length to be two based on the AIC. The results of the TY procedure reveal once more that energy consumption Granger causes CO₂ emissions at the 0.05 significance level
(\(\chi^2=6.713\)). Additionally, unidirectional causality is evident running from economic growth to CO\(_2\) emissions at the 0.05 level of significance (\(\chi^2=6.987\)) and unidirectional causality running from GDP to energy consumption at the 0.1 significance level (\(\chi^2=5.037\)).

Another version of the Granger causality test, the two-step Hsiao method which combines the Akaike’s Final Prediction Error (FPE) through a VECM approach, presents its results in Table 15. According to theory, the smallest value of FPE determines the optimal lag in both steps. Additionally, if \(FPE(l_{11}^*,l_{12}^*)\) (which results from the second step) is smaller than \(FPE(l_{11}^*)\) (which results from the first step) a causal relationship is evident. Hence, once more, there is causality running from energy consumption to CO\(_2\) emissions \((FPE(l_1^*)=0.000449 > FPE(l_1^*,l_{13}^*)=0.000333)\), but there is no evidence of any causal nexus concerning the opposite direction. In comparison to the previous causality tests, this particular one makes apparent that there is bidirectional causality between economic growth and CO\(_2\) emissions \((FPE(l_1^*)=0.000449, FPE(l_3^*)=0.000196 > FPE(l_1^*,l_{13}^*)=0.000354, FPE(l_2^*,l_{22}^*)=0.000191)\), as well as between economic growth and energy consumption \((FPE(l_3^*)=0.000252, FPE(l_2^*)=0.000196 > FPE(l_3^*,l_{32}^*)=0.000238, FPE(l_2^*,l_{22}^*)=0.000186)\). With no doubt, it is the test which, amongst the others that have been implemented, provides the most fruitful results.

5.5 Non-parametric causality tests

The Hiemstra and Jones (1994) [H&J] and Diks and Panchenko (2006) [D&P] procedures are used to identify whether any causal relationship is non-linear in the nature. This is the reason why these particular approaches are separated into three steps; the first concerns the implementation of the test on the growth rate of series, whereas in the second step, they are implemented to the de-linearized series via a VAR specification. The last step concerns a second moment filtering via a GARCH-BEKK model. Particularly, the results are clearly presented on Table 16 for the growth rates and Table 17 for the VAR residuals. On Table 18, the results of the second moment filtering are also illustrated.

To begin with the differenced series, the null hypothesis of no non-linear causality running from CO\(_2\) emissions to energy consumption is never rejected for both implemented tests. In fact, both tests provide similar outcomes. Concerning the causality running from CO\(_2\)
emissions to economic growth, the null hypothesis is only rejected in the seventh and eighth lag length at the 0.5 significance level and just for the H&J test. For the D&P test, the null hypothesis is still never rejected. When causality runs from energy consumption to GDP for both tests, the null hypothesis is rejected for the first three lag lengths in the 0.05 and 0.1 levels of significance.

In an attempt to examine the causality running to the opposite direction, it is observed that null hypothesis is scarcely rejected in each one of the cases. More specifically, for causality running from energy consumption to CO₂ emissions the null hypothesis is rejected, for both the implemented tests for the third lag length, in 0.05 and in 0.1 significance level for the H&J and D&P tests respectively. With regard to the causality that runs from GDP to CO₂, for the H&J test the null hypothesis is rejected, for the first and third lag length in 0.05 and for the second lag length in 0.01, while for the D&P test, is rejected for both the first and second lag length in the 0.05 significance level. Lastly, in the case of causality running from economic growth to energy consumption the null hypothesis is never rejected with the only exception to be for the H&J test, for the second lag length in the 0.1 level of significance.

As far as the de-linearized series are concerned, the results presented in Table 17 indicate that under the same null hypothesis, the previously mentioned evidence of causality that seemed as scarce now does not even exist. For both tests and each one of the causality directions between the time-series, the null hypothesis is never rejected at any of the lag lengths. The only one exception where the null hypothesis is rejected becomes evident for the D&P test for the first lag length when causality runs from economic growth to energy CO₂ emissions at the 0.1 significance level.

Last but not least, the second moment filtering reveals an interesting range of various results regarding the different tests and directions. Particularly, for causality running from CO₂ emissions to energy consumption the null hypothesis is rejected for the fourth to the seventh lag length at the 0.05 significance level while for the eighth lag length, is rejected at the 0.1 level of significance for the H&J test. For causality running to the opposite direction, means from energy consumption to CO₂ emissions, the null hypothesis is rejected for the fourth and fifth lag lengths at the 0.05 significance level and for the sixth and seventh lag lengths at 0.1 for the D&P test. When causality runs from energy consumption to CO₂ emissions for the H&J test, the null hypothesis is rejected at the fifth and sixth lag lengths at
the 0.1 significance level whereas for the D&P test, is rejected for the fifth lag lengths again at the 0.1 level of significance. Now, concerning the causality running from CO₂ emissions to economic growth the null hypothesis is rejected for the second lag length at the 0.05 level of significance for the H&J test and at the 0.1 for the D&P test. Rejection of the null is also evident when causality runs from economic growth to CO₂ emissions for the fourth and fifth lag lengths at 0.05 and 0.1 significance levels, respectively, for the H&J test as well as for the fourth lag length at the 0.05 significance level for the D&P test. Finally, with regard to the causality running from energy consumption to economic growth, there is no evidence of the rejection of the null hypothesis at any of lags and the tests. Contrariwise, for the opposite direction the null hypothesis is rejected for the third, fourth, seventh and eighth lag lengths at the 0.1 significance level, while for the fifth lag at the 0.01 level and for the sixth at the 0.05 level of significance for the H&J test. Regarding the D&P test, the null is rejected at the fifth lag length at the 0.05 significance level as well as for the seventh lag at the 0.1 significance level.

6. Policy recommendations

Given the fact that several causality tests were implemented in the study, while the data are related to a global level, the combining results concerning the variables under examination are as follows: a unidirectional causality is evident running from energy consumption to CO₂ emissions is evident for all of the causality tests; a bidirectional causality exists between energy consumption and CO₂ emissions and lastly, causality running once more in both directions is apparent between economic growth and CO₂ emissions. It is of great importance to mention that since the analysis is in a global basis, the policies must be carefully selected. Whatever the results, the distinction of the world into developed and developing countries hides tremendous differences that need to be taken into consideration for the implementation of every potential policy. The Table below presents the results of the causality tests that implemented in the dissertation.
The interpretations and implications of the empirical results can be further discussed in three aspects. In a first place, the empirical results of the study suggest the existence of unidirectional causality running from energy consumption to CO₂ emissions with no feedback. Hence, in a worldwide level, it is not evidently possible to meet an increasing energy demand without depending on energy sources and thus, CO₂ emissions inevitably increase (Alam, 2012). To this end, the reduction of energy consumption via the implementation of appropriate strategic plans by policy makers seems to be the most suitable way to reduce CO₂ emissions.

The global rate of CO₂ emissions is obtained from an aggregation, mainly, of developed as well as of developing countries (which can be separated in country-groups depending on parameters such as energy consumption) that consume any form of energy. As a consequence, every policy related to the control of the global emissions must pay attention to the specific country-group emission rates and their changes over time (Coondoo and Dinda, 2002). It is widely known from the United Nation’s Framework Convention on Climate Change (UNFCCC) that “the largest share of historical and current global emissions of greenhouse gases has originated in developed countries, that per capita emissions in developing countries are still relatively low and that the share of global emissions originating in developing countries will grow to meet their social and development needs” (Szklo et al., 2005). Hence, it is clear that the developed countries are those which contribute to global pollution at its greatest part, whereas the developing countries are those which suffer the consequences of the pollution. With no doubt, the results differ from one country to another according to the importance that energy sources have in an economy. Technological improvements in the developed countries are those that make the distinction evident, since they are the reason why there is an increase of emissions but on the other hand, they are those that can mitigate emissions by the implementation of new and environmental friendly sources and technologies. This was the motivation for the UNFCCC to make the separation distinct.
between the developed countries, or else those that are listed to the Annex-I\textsuperscript{3} parties to the Convention, and the developing countries, or else those that are listed to the Non-Annex I parties.

Under the Kyoto protocol, the developed countries agreed to mitigate their greenhouse-gas emissions to the levels that emitted back in 1990’s. Due to the fact that the CO\textsubscript{2} molecules have a long life (about 100 years) the phenomenon of global warming should be confronted by the control of the emissions’ growth for a cleaner global environment. For this purpose, the United Nations’ Kyoto protocol established binding greenhouse-gas emissions’ reduction targets for industrialized countries and the European community. To help achieve these targets, the protocol introduced three "flexible mechanisms" in order to offer the opportunity to increase the flow of technology and finance to the environment and energy area and assist in promoting sustainable development; international emissions’ trading, joint implementation, and the clean development Mechanism. These mechanisms introduce a system of tradable permits for CO\textsubscript{2} emissions against compensatory payments at an international level.

The second aspect concerns the bidirectional causality or feedback between energy consumption and economic growth. When there is causality running in both directions for these two variables, the higher the level of economic growth, the higher the level of energy demand and vice versa. Such an increase in energy consumption would lead once more to a subsequent increase in the emissions and pollution of the environment. Hence, some policy advice should contain new ways of reducing energy demand from the consumers in order not to adversely affect economic growth. Policies such as taxes and subsidies to consumers as well as the adoption of technology that minimizes environmental pollution seem to be most appropriate for this reason. Undoubtedly, these are policies that fit in developed countries where the standard of living is high and as a result the energy consumption per capita is high as well. The advancement of the developed countries’ economies brought these results that are responsible for further energy consumption in all the various sectors that these countries contain (industrial sector, commercial sector, transformation, households, etc.). It is called common logic that the higher the disposal economic growth in a country, the higher the energy consumption is. With regard to the developing countries, the more suitable policies are

\textsuperscript{3} The Annex I Parties to the UNFCCC are Australia, Austria, Belarus, Belgium, Bulgaria, Canada, Croatia, Czech Republic, Denmark, Estonia, European Union, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Russian Federation, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom of Great Britain and Northern Ireland, and the United States of America.
those that give emphasis on the improvement of sustainable energy supply on the one hand, while reduce poverty on the other.

Next, the third aspect regarding the bidirectional causality between economic growth and CO₂ emissions gives reasons for policy options that have to reduce emissions by imposing limiting factors on economic growth as well. Given the fact that bidirectional causality exists, as far as economic growth increases (or decreases), further CO₂ emissions are stimulated in higher (or lower) levels and thus, a potential reduction of the emissions should have an adverse effect on economic growth. Due to the fact that the CO₂ emissions generate externalities at a global level affecting mankind universally, the evident bidirectional causality can be dealt with the next policies (Coondoo and Dinda, 2002). In a first place, governments of the entire developed countries have to consider the reduction of energy consumption by the implementation of some serious environmental policies that will benefit the environment. As a result, measures should be taken in order to encourage governments and industries to make investments on the reduction of emissions without affecting economic growth negatively. Such policies are, for instance, those technological changes that convert the already existing ones to be more environmental friendly. Contrariwise, alternative policies that decrease energy intensity, increase energy efficiency obtained from the use of renewable technologies as well as the utilization from the use of cleaner energy sources (solar, wind, geothermal, etc.) can mitigate environmental degradation and extend the time until new technologies allow the complete switch from fossil fuels to cleaner energy sources (Soytas et al., 2007).

To conclude, it is of utmost importance to mention that the European Union has made a first attempt for the implementation of some of the aforementioned policies via the known as the "20-20-20" targets which set three key objectives for 2020: i) to reduce greenhouse-gas emissions by 20%; ii) to increase the energy consumption but from energy produced by renewable resources and finally iii) to improve the EU’s energy efficiency by 20%.
7. Conclusions

This dissertation has attempted to empirically analyze the causal relationship between CO$_2$ emissions, energy consumption and economic growth in a worldwide level. For this purpose, a number of linear and non-linear causality tests were implemented in order to end up with the desirable results.

To briefly outline the main points of the study, in a first step, unit root tests were applied to investigate whether the variables in the study are integrated of order zero or one. The ADF test, the GLS-DF test and the PP test revealed that all of the variables under investigation were integrated of order one, provided that we failed to reject the null hypothesis in levels in every case. Conversely, when these tests were applied not in the levels but in the first differences of the time series, the null hypotheses were rejected. In other words, the three variables are stationary in their first differences. Moreover, the null hypothesis was clearly and consistently rejected at the 0.01 level of significance. The same order of integration is identified by the remaining KPSS stationarity test. Apart from these unit root tests, two additional (ZA and Perron unit root tests) were conducted so as to detect if there were unit roots with breaks, or not. In this case, the results revealed that in general, neither the break in the intercept nor slope, nor both were statistically significant for the variables since we failed to reject the null hypothesis. Only for CO$_2$ emissions, stationarity under one break could be detected. It was the only case where the null hypothesis was rejected at the 0.01 level of significance. The statistically significant break was in 2003 for CO$_2$ emissions. For the additional KSS unit root test, which is characterized as a non-linear unit root test, the variables, once more, were I(1). The null hypothesis was steadily failed to be rejected.

Afterwards, some tests to detect whether cointegration exists or not, took place. Evidence from the Johansen cointegration test showed that the null hypothesis of zero cointegrating relationships was not rejected at any conventional level of significance and hence, there is no cointegration. The Engle and Granger cointegration test gave results that rejected the null hypothesis as well and thus, neither for this test, cointegration was evident between the variables. Concerning the ARDL bounds testing approach, the computed $F$-Statistics by the Wald test are compared with the critical values provided by Narayan (2005) since the sample size of the study is small while the results confirm the absence of cointegration. As a whole, what is obtained is a conclusion with no evidence of cointegration for any of the tests.
Another step that follows is the BDS test, the non-linear dependence test applied on residuals that assesses the i.i.d. (independent and identically distributed) assumption on the de-linearized time-series data. The results revealed that the i.i.d. assumption was consistently rejected, irrespectively of the imposed dimension, for different levels of significance. Hence, the results apparently reveal that non-linearity exists and the non-linear causality tests are the most appropriate to be implemented.

Then, the time for examining causality has come. In order to investigate the presence of linear causality between the variables three of the most well-known causality tests were implemented, namely, the standard Granger causality test and the TY approach. With regard to the Granger causality test, the results showed that there is unidirectional causality running from energy consumption to CO₂ emissions at the 0.05 level of significance ($F=9.760$). This was the only causality detected between the three variables since there is no evidence for other relationships at the $F$-Statistics. The results of the TY procedure revealed once more that energy consumption Granger causes CO₂ emissions at the 0.05 significance level ($\chi^2=6.713$). Additionally, unidirectional causality is evident running from economic growth to CO₂ emissions at the 0.05 level of significance ($\chi^2=6.987$) and unidirectional causality running from GDP to energy consumption at the 0.1 significance level ($\chi^2=5.037$). For the Hsiao method, the results indicated that there is causality running from energy consumption to CO₂ emissions for third time, with no feedback. Furthermore, compared to the previous causality tests, this particular one made apparent that there is bidirectional causality between economic growth and CO₂ emissions as well as between economic growth and energy consumption.

According to these results, a vast amount of policies should be adopted, of course, depending on the country’s economy. Strategic plans such as the use of renewable technologies as well as the utilization from the use of cleaner energy sources (solar, wind, geothermal, etc.) can mitigate environmental degradation, decrease energy intensity and increase energy efficiency. Governments of the entire developed countries have to consider the reduction of energy consumption by the implementation of some serious environmental policies that will benefit the environment. As a result, measures should be taken in order to encourage governments and industries to make investments on the reduction of emissions without affecting economic growth negatively. Additionally, technological improvements in the developed countries are those that make the distinction evident, since they are the reason
why there is an increase of emissions but on the other hand, they are those that can mitigate emissions by the implementation of new and environmental friendly sources and technologies. Eventually, some policy advice should contain new ways of reducing energy demand from the consumers in order not to adversely affect economic growth. Policies such as taxes and subsidies to consumers as well as the adoption of technology that minimizes environmental pollution seem to be most appropriate for this reason.

Last but not least, it is of rather interest to mention that the subject under discussion could be further developed if every available data were obtained separately for each one of the developed and developing countries. The existence of a vast amount of data could possibly result in more precise results.
References


Appendix

Countries with commitments under the Kyoto Protocol in order to limit or reduce greenhouse gas emissions must meet their targets primarily through national measures. As an additional means of meeting these targets, the Kyoto Protocol introduced three market-based mechanisms. The CO2, which is now presented as a new commodity, is traded and tracked like any other commodity instituting the “CO2 market.” In more detail the Kyoto mechanisms are:

<table>
<thead>
<tr>
<th>Mechanism</th>
<th>Description</th>
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<tr>
<td>Clean Development Mechanism (CDM)</td>
<td>It is one of the &quot;flexibility&quot; mechanisms defined in Article 12 of the Kyoto Protocol. The stated purpose of the mechanism is to help developing countries achieve sustainable development, and assist industrialized countries (Annex B Party) in complying with their emission reduction commitments. The CDM allows industrialized countries to invest and implement an emission-reduction project in developing countries. In order to comply with their emission limitation targets, Certified Emission Reductions (CERs), each equivalent to one tonne of CO2, are used as a type of emissions unit. It is considered as the first global, environmental investment and credit scheme of its kind.</td>
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<tr>
<td>Joint Implementation (JI)</td>
<td>It is the second mechanism defined in Article 6 of the Kyoto Protocol. Under this mechanism, project activity is allowed among developed countries as well as between developed and developing countries. More specifically, it allows a country with an emission reduction or limitation commitment under the Kyoto Protocol (Annex B Party) to</td>
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<tr>
<td><strong>International Emissions Trading (IET)</strong></td>
<td>earn emission reduction units (ERUs) from an emission-reduction or emission removal project in another Annex B Party. Each ERU is equivalent to one tonne of CO$_2$. In general, Joint Implementation is a flexible and cost-efficient mechanism that offers Parties an efficient way to meet their Kyoto commitments, whereas the host Party benefits from foreign investment and technology transfer.</td>
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<tr>
<td>The last mechanism is the one defined in Article 17 of the Kyoto Protocol. This mechanism differs to the other two abovementioned since it allows countries that have emission units to spare (emissions permitted them but not “used”) to sell this excess capacity to countries that are over their targets. The levels of allowed emissions, or else “assigned amounts” which can be interpreted as the targets for limiting or reducing emissions for Annex B Parties, are divided into “assigned amount units” (AAUs).</td>
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