Energy Consumption and Economic Growth: Parametric and Non-Parametric Causality Testing for the Case of Greece

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Abstract

The objective of this paper is to contribute to the understanding of the linear and non-linear causal linkages between total energy consumption and economic activity, making use of annual time series of Greece for the period 1960-2008. Two are the salient features of our study: first, the total energy consumption has been adjusted for qualitative differences among its constituent components through the thermodynamics of energy conversion. In doing so, we rule out the possibility of a misleading inference due to aggregation bias. Second, the investigation of the causal linkage between economic growth and the adjusted for quality total energy consumption is conducted within a non-linear context. Our empirical results reveal significant unidirectional both linear and non-linear causal linkages running from total useful energy to economic growth. These findings may provide valuable information for the contemplation of more effective energy policies with respect to both the consumption of energy and environmental protection.

JEL Classification: C14, C22, Q43, Q48.
Keywords: Energy consumption; Economic growth; Non-linear causality.

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1 Introduction

This paper aims at uncovering the possible linear or non-linear causality between total energy supply and economic activity using annual data from the Greek economy spanning the period between 1960 and 2008. Our analysis is much broader than that of previous studies on the Greek economy (for reviews see *e.g.*, Dergiades and Tsoulfidis (2011)) as it includes besides electricity all other energy flows used within the Greek energy system. The characteristic difference of our study from other previous international ones is the homogenization of energy inputs in such that to account for their differential efficiencies and in so doing we end up with an altogether new series of quality adjusted energy consumption known as total useful energy. Furthermore, our analysis of the causal linkages between economic growth and the quality adjusted total energy consumption is carried out within a non-linear context.

Four are the outcomes or testing hypotheses of the causality (linear or nonlinear) analysis, between energy consumption and economic activity: a) the growth hypothesis, b) the conservation hypothesis, c) the neutrality hypothesis and finally d) the feedback hypothesis. Each of the above mentioned hypotheses implies a different kind of economic policy. In particular, the first hypothesis is referred to the existence of a unidirectional causality running from the energy consumption to economic growth, suggesting that disruptions or restrictions in the smooth supply of energy in the economy will exert a negative impact on economic growth. On the other hand, non-conservation energy policies are expected to influence positively economic growth. By contrast, the second hypothesis implies that there is unidirectional causality running from economic growth to energy consumption. The policy implication of the conservation hypothesis is that as the economy is not entirely energy dependent, the government may adopt energy conservation policies with minimal effects on economic growth. The third hypothesis refers to the case, where there is no causality running in either direction, and, therefore, any policy with respect to the consumption of energy, conservative or expansive, is expected to have a negligible effect on economic growth. Finally, the fourth hypothesis suggests a bidirectional causal relationship between energy consumption and economic growth thereby lending support to the view that a mix of taxation and subsidization policies may exert a positive growth effect in the economy without influencing, at the same time, the effectiveness of the implemented energy conservation policies. As a consequence, the empirical findings related to the causality direction, may be extremely useful for the appraisal of the effectiveness of various energy policies.

The novelty of our study is that it bridge's a lacuna in the literature by combining non-linear causality techniques along with the use of a quality-weighted scheme in constructing the total energy consumption series for the Greek economy. To the extent that we know the literature there are no previous studies combining non-linear causality techniques along with the use of a quality-weighted scheme in the construction of the total energy consumption series. The energy quality adjustment approach adopted in this paper is in accordance with the influential study of Cleveland et al. (2000), who argued that in "aggregating different energy types by their heat units embodies a serious flaw: it ignores qualitative differences among energy vectors" as well as that "adjusting energy for quality is important as is considering the context within energy use is occurring". This view, for energy quality adjustment, is further acknowledged and supported by Zachariadis (2007), who argued that such practice has to be seriously considered in similar empirical applications. Moreover, our methodological framework is in line with the conclusion of Ozturk (2010) who noted that "it should be understood that research papers using the same methods with the same variables, just by changing the time period examined, have no more potential to make contribution to the existing energy-growth literature". In particular, apart from the usual implementation of the standard Granger causality test (Granger, 1969); we applied the well known non-parametric Hiemstra and Jones (1994) test for non-linear causality as well as its recent modification, proposed by Diks and Panchenko (2006).

In order to aggregate the various heterogeneous sources of energy particular care should be applied when we accounting for their differential efficiencies. In this sense, we took in consideration the efficiency adjustments in the energy mix used in the economy over time, since by definition the total useful energy measures the capacity of the various energy flows to perform useful work. There are many approaches that can be used in order to account energy for quality, such as for example production side approaches (characterized in the literature as emergy) or end-use approaches (known as exergy or the price-based approach).[1] Ideally, it would be absolutely desirable to compare the results of our analysis with those that would be derived had we followed an economically meaningful way to homogenize the energy flows, that is, through prices. The idea is that prices reflect both preferences and productivities. The trouble with such an approach is that the data on prices for so many diverse energy input sources are hard to come by for such a long period of time. Furthermore, prices in energy markets do not necessarily reflect preferences or productivities simply because of heavy government regulation of the energy industry. Consequently, prices are fraught with a number of taxes and restrictions and so they do not reflect only preferences and productivities. Finally, the use of prices for the purposes of aggregation of various energy sources to a single one is based on the implicit assumption that the substitutability among the various fuels is unaffected by the magnitude of the non-fuel inputs used (Cleveland et al., 2000), a very strong assumption in some cases.[2]

The remainder of the paper is organized as follows: Section 2 reviews briefly the literature on the nexus between energy consumption and economic growth. Section 3 continues with the presentation of the adopted methodological framework. Section 4 discusses basic data issues and at the same time conducts the necessary preliminary econometric analysis. Section 5 presents and evaluates the results of the causality testing procedure and finally, Section 6 summarizes and draws some broad policy conclusions.

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[1] Cleveland (1992) provides a comprehensive and insightful discussion of the concept of energy quality.

[2] According to Cleveland (1992) there is no single method of aggregation generally and unequivocally accepted among researchers, there are pros and cons in each research method.

2 Review of the Literature

In recent decades there are many studies contributing to the understanding of the nexus between energy consumption and economic growth. Ozturk (2010) provides a pretty detailed chronological survey of studies investigating, for a single country or for a group of countries, the causal relationship between energy consumption and economic growth. Therefore, our focus concentrates exclusively on relevant and recently published papers, whose results are conveniently summarized in Table 1 below. We observe that the results of Table 1 are by no means uniform and they vary across countries in the same level of economic development but also for the same country in different time periods and econometric methodologies utilized each time. The lack of uniformity in the results stems, among other things, from the different estimating methods, sample periods, quality of data and model specifications. Furthermore, it is worth noting that the results in most of past studies suffer from the assumption of linearity in the variables involved, while in effect the relations between variables might be nonlinear in character. Meanwhile, various economic shocks and regime changes, such as for example those emanating from economic environment, energy policies and variations in energy price may give rise to such structural changes in energy consumption for the time period under study rendering the assumption of linearity utterly misleading. Clearly, such structural changes in energy consumption and economic growth may be described much more accurately by a non-linear relationship, and therefore the non-linear modelling may be more suitable to the task at hand (Lee and Chang, 2005). The results of most recent studies are displayed in Table 1 below.

A cursory look at Table 1 reveals the country specific empirical results. For example, starting with the study by Tsani (2010) using data from the Greek economy spanning the period 1960-2006 and the Toda-Yamamoto causality test finds unidirectional causality running from the total energy consumption to real GDP, while different causal relationships are identified at disaggregated levels (not shown in Table 1). The same methodology (the Toda-Yamamoto test), when applied to the economy of China for the period 1960-2007, gives quite opposite results with causality running from real GDP to energy consumption (Zhang and Cheng, 2009). The same test does not identify any causal relationship in the USA during the period 1949-2006 according to Bowden and Payne (2009). Similar are the results for the Turkish economy (1960-2005) according to Halicioglu (2009), who is using an ARDL cointegration methodology and a VECM for testing causality. The study by Chiou-Wei et al. (2008) implements for each of eight Asian economies and the USA the non-linear Hiemstra and Jones (1994) causality test. More specifically, Chiou-Wei et al. (2008) identify causality running from energy to real GDP for Taiwan (1954-2006) and Hong Kong (1971-2003). While, opposite results are derived for Singapore (1971-2003) and Philippines (1971-2003). Their analysis for Korea (1971-2003), Malaysia (1971-2003), Thailand (1971-2003) and the United States (1960-2003) showed no causality to any direction and finally, for Indonesia the results confirmed bidirectional causality.

Hondroyiannis et al. (2002) in their analysis for Greece (1960-1996) implemented the Johansen cointegration technique and the VECM causality framework as well as Ghali and El-Sakka (2004) under the same methodology for the Canadian economy (1961-1997), both found bidirectional causality between energy consumption and GDP. However, when Cleveland et al. (2000) employed the standard Granger causality test, in a bivariate as well as in a multivariate framework, to the US economy (1947-1996) they reached inconclusive results. In particular, the bivariate causality tests showed no relation between the two variables even in the case when energy consumption was adjusted for quality. Different and conflicting results were obtained in the multivariate Granger causality tests, where real GDP was found to Granger cause energy consumption, and when the test was repeated using energy consumption adjusted for quality, the arrow of causality run the opposite direction.

Table 1: Brief summary of the recent literature

Source	Country	Period	Methodological Framework	Causality inference
Panel A−Country specific studies				
Tsani (2010)	Greece	1960 – 2006	Toda−Yamammoto causality test	$E \rightarrow Y$
Zhang and Cheng (2009)	China	1960 – 2007	Toda−Yamammoto causality test	$Y \rightarrow E$
Bowden and Payne (2009)	United States	1949 – 2006	Toda−Yamammoto causality test	$Y \nleftrightarrow E$
Halicioglu (2009)	Turkey	1960 – 2005	ARDL cointegration, VECM causality	$Y \nleftrightarrow E$
Chiou−Wei *et al.* (2008)	Taiwan	1954 – 2006	Hiemstra−Jones causality test	$E \overset{\sim}{\rightarrow} Y$
≫	Hong Kong	1971 – 2003	Hiemstra−Jones causality test	$E \overset{\sim}{\rightarrow} Y$
≫	Korea	1971 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\nleftrightarrow} E$
≫	Singapore	1971 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\rightarrow} E$
≫	Indonesia	1971 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\leftrightarrow} E$
≫	Malaysia	1971 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\nleftrightarrow} E$
≫	Philippines	1971 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\rightarrow} E$
≫	Thailand	1971 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\nleftrightarrow} E$
≫	United States	1960 – 2003	Hiemstra−Jones causality test	$Y \overset{\sim}{\nleftrightarrow} E$
Ghali and El−Sakka (2004)	Canada	1961 – 1997	Johansen cointegration, VECM causality	$Y \leftrightarrow E$
Hondroyiannis *et al.* (2002)	Greece	1960 – 1996	Johansen cointegration, VECM causality	$Y \leftrightarrow E$
Cleveland *et al.* (2000)	United States	1947 – 1996	Bivariate Granger causality	$Y \nleftrightarrow E$
≫	United States	1947 – 1996	Bivariate Granger causality	$Y \nleftrightarrow E^q$
≫	United States	1947 – 1996	Multivariate Granger causality	$Y \rightarrow E$
≫	United States	1947 – 1996	Multivariate Granger causality	$E^q \rightarrow Y$
≫	United States	1947 – 1996	Johansen cointegration, VECM causality	$Y \rightarrow E$
Panel B−Group country studies				
Huang *et al.* (2008)	Low income group countries (N= 19)	1972 – 2002	Panel VAR causality	$Y \nleftrightarrow E$
≫	Lower middle income group countries (N= 22)	1972 – 2002	Panel VAR causality	$Y \rightarrow E$
≫	Upper middle income group countries (N= 15)	1972 – 2002	Panel VAR causality	$Y \rightarrow E$
≫	High income group countries (N= 26)	1972 – 2002	Panel VAR causality	$Y \overset{-}{\rightarrow} E$
≫	All countries (N= 82)	1972 – 2002	Panel VAR causality	$E \rightarrow Y$
Narayan and Smyth (2008)	G7 countries	1972 – 2002	Panel cointegration, Panel causality test	$E \rightarrow Y$

Notes: The single direction arrow ($\rightarrow$) signifies that the causality is running from the left hand side variable to the right hand side variable. The double direction arrow ($\leftrightarrow$) denotes the presence of bidirectional causality between the involved variables. The deleted double direction arrow ($\nleftrightarrow$) indicates the absence of causality in any direction. The tilde symbol above any kind of arrow ($\sim$) points out that the identified (or not) causality is non-linear in nature. The exponent q in the energy consumption variable (E) implies that total consumption has been adjusted for quality differences among alternative energy flows. The minus symbol above an arrow ($\overset{-}{\rightarrow}$) shows that the causality between the involved variables is negative. Finally, N is the number of countries which are included in each income group.

No more definitive were the results derived from studies implementing panel analysis. Thus, in Huang et al. (2008) study of panel VAR causality their results for the period 1972-2002 and 19 low income group countries showed no causality to either direction, whereas for the 37 countries in the middle income group causality was from the real GDP to energy consumption. The results for the 26 high income group countries revealed, once again, causality running from real GDP to energy consumption with the difference that the sign of causality was negative. When the authors combined all 82 countries to a single test the results yielded causality running from energy to real GDP. The same result was derived by Narayan and Smyth (2008) in their study for the G7 countries for the period 1972-2002.

3 Methodology

3.1 The standard Granger causality test

The standard Granger (1969) causality test identifies the existence of a possible causal relationship between two variables. Within a VAR framework the null hypothesis of no causality is tested via the significant contribution that past values of one variable can offer in predicting current values of another variable. Illustration of the details related to the implementation of the standard Granger causality test, apart from the seminal articles of Granger (1969) and Sims (1972), can be found in several studies in the literature (see for example Chiou-Wei et al. (2008), *inter alia*). In cases where cointegration is verified in the levels of the involved variables, then the VAR equations are augmented with the inclusion of the error correction term. In such case, the causality testing procedure takes place within the VECM framework (Engle and Granger, 1987).

3.2 A non-linear causality testing

The standard Granger causality testing procedure is inappropriate to detect the presence of a non-linear causal relationship between two series. As Baek and Brock (1992) have pointed out, the power of the tests conducted within a linear framework is lower compared to those conducted within a non-linear alternative. To circumvent the limitations of the linear framework our attention shifts to the two modified versions of the Baek and Brock (1992) testing procedure proposed by Hiemstra and Jones (1994) and Diks and Panchenko (2006).[3]

3.2.1 Testing for non-linear dependence

Before testing for non-linear causality it is of great importance to confirm the presence of non-linearity in the series at hand. In particular, in our effort to identify potential deviations from the assumption of independence, the BDS test is being applied as suggested by Brock et al. (1996). The BDS test can be implemented to the residuals derived from the delinearization of the series (*e.g.* residuals computed from a VAR specification), in order to ascertain whether or not these residuals are i.i.d. (independent and identically distributed). To this end, it should be established, for any given pair of observations, that the probability of their distance being less than or equal to θ (a randomly selected small positive number), remains constant.

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

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

where, the indicator function $I\left(Z^{\kappa}_{t+j}, Z^{\kappa}_{s+j}\right)$ takes on the value of 1 if $\|Z^{\kappa}_{t}, Z^{\kappa}_{s}\| \leq \theta$ and 0

[3]It goes without saying that this section is based on Hiemstra and Jones (1994) and Diks and Panchenko (2006).

otherwise, $\|Z_t^\kappa, Z_s^\kappa\|$ denotes the Euclidean distance between Z_t^κ and Z_s^κ.

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

$$B = \left(\sqrt{n-\kappa+1}\right) \frac{\hat{C}_{\kappa,n}\left(\theta\right) - \hat{C}_{1,n-\kappa+1}(\theta)^{\kappa}}{S_{\kappa,n}\left(\theta\right)} \xrightarrow{D} N(0,1) \tag{2}$$

follows the standard normal distribution. Where, $S_{\kappa,n}\left(\theta\right)$ is the standard deviation estimator.

3.2.2 The Hiemstra and Jones test

The Hiemstra and Jones (1994) test restates the null hypothesis used by Baek and Brock (1992) in terms of joint distributions. In particular, for two strictly stationary and weakly dependent time series, G_t and E_t, consider the subsequent definitions: let $\mathbf{Z}_t^\kappa$ to be the κ-length lead vector of G_t, $\mathbf{E}_t^{l_e}$ the l_e-length lag vector of E_t and finally, $\mathbf{G}_t^{l_g}$ the l_g-length lag vector of G_t, with $l_e, l_g \geq 1$. Given that the null hypothesis is actually a proposition about the invariant distribution of the $(l_e + l_g + \kappa)$-dimensional vector $\mathbf{X}_t = (\mathbf{E}_t^{l_e}, \mathbf{G}_t^{l_g}, \mathbf{Z}_t^\kappa)$, the time subscript is dropped. It is also assumed, as a common empirical practise, that κ is equal to 1 and in the interest of brevity and clarity of presentation, we set $l_e = l_g = 1$. Therefore, given all the pre-mentioned definitions and assumptions, the null hypothesis of no causality should satisfy the following condition:

$$\frac{f_{E,G,Z}\left(e,g,z\right)}{f_{E,G}\left(e,g\right)} = \frac{f_{G,Z}\left(g,z\right)}{f_{G}\left(g\right)} \tag{3a}$$

or,

$$\frac{f_{E,G,Z}\left(e,g,z\right)}{f_{G}\left(g\right)} = \frac{f_{E,G}\left(e,g\right)}{f_{G}\left(g\right)} \frac{f_{G,Z}\left(g,z\right)}{f_{G}\left(g\right)} \tag{3b}$$

Hiemstra and Jones (1994) argued that for a randomly selected small positive value of θ, the non-Granger cause condition shown in equation (3.a), implies the following ratios of joint probabilities:

$$\frac{C_{E,G,Z}(\theta)}{C_{E,G}(\theta)} = \frac{C_{G,Z}(\theta)}{C_{G}(\theta)} \tag{4a}$$

or,

$$\frac{C_{E,G,Z}(\theta)}{C_{G}(\theta)} = \frac{C_{G,Z}(\theta)}{C_{G}(\theta)} \frac{C_{E,G}(\theta)}{C_{G}(\theta)} \tag{4b}$$

where, $C_{\mathbf{W}}(\theta)$, with $\mathbf{W}$ any arbitrary multivariate vector taking on values in $\mathbb{R}^{d_{\mathbf{W}}}$, denotes the probability of identifying two independent realizations of the $\mathbf{W}$ vector within a distance which is smaller than or equal to θ. The above illustrated ratios of the $C_{\mathbf{W}}(\theta)$ correlations integrals are in fact measures of divergence between the two sides of the (3.a) equality. The general formula for the $C_{\mathbf{W}}(\theta)$ correlation integral is given as follows:

$$\begin{aligned} &\mathrm{C}_W(\theta) = P\left[\|\mathbf{W}_1 - \mathbf{W}_2\| \leq \theta\right], \mathbf{W}_1, \mathbf{W}_2 \text{ indpen. } \sim \mathbf{W} \\ &= \int\int I\left(\|s_1 - s_2\| \leq \theta\right) f_N(s_1)\, f_N(s_2)\, ds_1 ds_2 \end{aligned} \tag{5}$$

where, $P[\bullet]$ denotes the probability function, $\|\bullet\|$ is the maximum norm, which for the n-dimensional vector $\mathbf{W} = \{W_1, W_2, ..., W_n\}^T$ is defined as $\|\mathbf{W}\| = \sup_{i=1}^{n} |W_i|$, $I\left(\|s_1 - s_2\| \leq \theta\right)$ is, as previously, the indicator function which takes on the value of 1, if $\|s_1 - s_2\| \leq \theta$ and 0 otherwise.

To assess statistically the validity of the non-causality condition in equation (4.a), Hiemstra and Jones (1994) utilized sample estimators for the approximation of the correlations integrals presented in (5). These estimators have the following form:

$$\hat{C}_{W,n}(\theta) = \frac{2}{n(n-1)} \sum_{i<j} \sum I_{ij}^{W} \tag{6}$$

Based on the above estimator, the two ratios of correlation integrals presented in equation

(4.a) can be substituted by their respective sample estimators adjusting equation (6) accordingly. As a result, for given values of κ, l_e, l_g and θ, the ratio difference of the correlation integrals estimators T, is proved by Hiemstra and Jones (1994) that follows the normal distribution.

$$T = \left[\frac{\hat{C}_{E,G,Z}(\theta, n)}{\hat{C}_{E,G}(\theta, n)} - \frac{\hat{C}_{G,Z}(\theta, n)}{\hat{C}_{G}(\theta, n)} \right] \sim N\left(0, \frac{1}{\sqrt{n}} \sigma^2 (\kappa, \mathrm{l}_e, \mathrm{l}_g, \theta)\right) \tag{7}$$

3.2.3 The Diks and Panchenko modification

The major shortcoming of the Hiemstra and Jones (1994) test is that over-rejects, in certain situations, the null hypothesis when this is actually true. Diks and Panchenko (2006) argued that the observed over-rejection of the null hypothesis comes from the assumption made by Hiemstra and Jones (1994), that equation (3.a) implies equation (4.a). As a result, Diks and Panchenko (2006) made an effort to remedy this inconsistency by introducing a modified Statistic and in so doing the null hypothesis can be restated as follows:

$$q \equiv E\left[f_{E,G,Z}(E, G, Z) f_G(G) - f_{E,G}(E, G) f_{G,Z}(G, Z)\right] = 0 \tag{8}$$

and the proposed estimator for q is:

$$T_n(\theta_n) = \frac{(2\theta)^{-d_E - 2d_G - d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k, k \neq ij} \sum_{j \neq i} \left(I_{ik}^{EGZ} I_{ij}^{G} - I_{ik}^{EG} I_{ij}^{GZ} \right) \right] \tag{9}$$

where, $I_{ij}^X = I(\|\mathbf{X}_i - \mathbf{X}_j\| \leq \theta)$, with $I(\bullet)$ to be the indicator function and θ_n the bandwidth which depends on the sample size. The vector $\mathbf{X}$ is defined as previously.

Hence, if we denote as $\hat{f}_X(\mathbf{X}_i)$ the local density estimator of the vector $\mathbf{X}$ at $\mathbf{X}_i$, that is:

$$\hat{f}_X(\mathbf{X}_i) = (2\theta_n)^{-d_X}(n-1)^{-1}\sum_{j,j\neq i} I_{ij}^X \tag{10}$$

Then, the $T_n(\theta_n)$ Statistic can be expressed in the following compact form:

$$T_n(\theta_n) = \frac{(n-1)}{n(n-2)}\sum_i \left(\hat{f}_{E,G,Z}(E_i, G_i, Z_i)\,\hat{f}_G(G_i) - \hat{f}_{E,G}(E_i, G_i)\,\hat{f}_{G,Z}(G_i, Z_i)\right) \tag{11}$$

Diks and Panchenko (2006) showed that if $\theta_n = Cn^{-\beta}$ with $\left(C > 0, \frac{1}{4} < \beta < \frac{1}{3}\right)$, then the distribution of the $T_n(\theta_n)$ Statistic converges to the standard normal:

$$\sqrt{n}\frac{(T_n(\theta_n) - q)}{S_n} \xrightarrow{D} N(0,1) \tag{12}$$

where, S_n is the asymptotic variance estimator of $T_n(\bullet)$. Overall, through the implementation of the Statistic illustrated in equation (12), the risk of over-rejecting, the null of no causality, is reduced, and therefore the major drawback of the (Hiemstra and Jones, 1994) non-linear hypothesis testing procedure is taken care of.

4 Data sources and preliminary analysis

4.1 Data sources

This study makes use of annual time series data for the economy of Greece, covering the period from 1960 to 2008. The length of the period under study is determined by the availability of the data. The variables at hand are the real gross domestic product (2000=100) and the quality adjusted total energy consumption (in tonnes of oil equivalent). The data on

GDP come from the World Development Indicators (WDI) databank of the World Bank;[4] while the energy consumption variable has been constructed utilizing detailed raw data from the energy balances statistics of the International Energy Agency (IEA)[5] and the Greek National Energy Information System.[6]

As it has been already pointed out, most empirical studies in the field simply aggregate the alternative energy flows according to their respective heat units.[7] The problem with the method of simple aggregation in terms of heat units is that it may give rise to serious biases when one does not account for qualitative differences among different energy sources and furthermore downplays the importance of the technological progress in the processes and the devices used for energy transformation. As a consequence, our focus lies on the construction of the total useful energy series, where qualitative differences among different energy flows are accounted for. Technological progress, as this can be expressed by efficiency, affects not only the extraction of various energy forms but also the practices associated with the intermediate conversion and transfer. Replacement investments along with technological improvement in the processes and the equipment, affect the quantitative and the qualitative characteristics of the final used energy.

In this work, the effects of the technological progress together with changes in the composition of the energy mix are taken into account in the estimation of the total useful energy, in terms of tons of oil equivalent, for the Greek energy system. Total useful energy is equal to the final energy (energy supplied to a process or equipment) minus the conversion loses. Our calculations are based on efficiency factors taking into account all the possible combinations that may arise between final energy forms and end-uses. Additionally, in order to increase the accuracy of our estimations of the total useful energy series, the Greek energy system has been divided in 12 sectors.[8] In each sector, the transformation from one energy form

[4]See http://databank.worldbank.org

[5]See http://www.iea.org

[6]See http://www.ypan.gr

[7]Among the few exceptions are included the studies by Berndt (1996), Stern (1993) and Patterson (1996).

[8]The 12 sectors of the Greek energy system are the following: primary energy production, net imports, bunkers, transformations, energy sector, industrial sector, transportation (air, land, sea and rail), agricultural

to another is characterized by a specific efficiency factor that depends not only on time but also on the energy form used and the technology employed. As a result, the total useful energy use ($\mathscr{U}$) for the Greek energy system and for a given period, it can be approximated through the following formula:

$$\mathscr{U} = \sum_{i=1}^{k} \sum_{j=1}^{l} \sum_{\lambda=1}^{\pi} \mathscr{F}_{i,j,\lambda} \mathscr{Q}_{j,\lambda} \tag{13}$$

where, i denotes the sector, j is the energy form, λ is the transformation technology, ($\mathscr{F}$) is the final energy and finally, ($\mathscr{Q}$) is the quality factor as this can be depicted through efficiency. For the entire Greek energy system, the final total useful energy series, for a given period, is constructed by aggregating the useful energy used by the following sectors of the economy: energy, industrial, agricultural, commercial, residential and transportation.[9] Figures 1 and 2 below illustrate the two key variables of the study, the total useful energy of the Greek economy in tonnes of oil equivalent[10] and the gross domestic product (GDP) in constant prices (2000=100), for the period 1960-2008.

Figure 1: Total Useful Energy

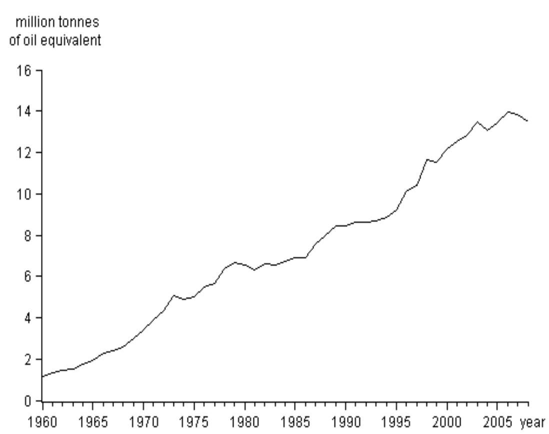
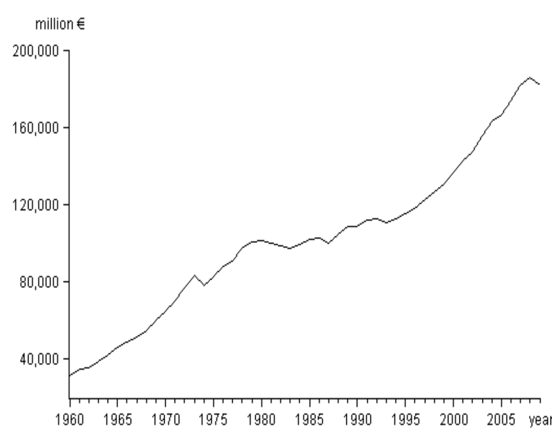


Figure 2: Real Gross Domestic Product



sector, commercial sector, residential sector, non energy uses and finally all other.

[9]A more detailed discussion about the construction of the total useful energy series is provided in the appendix.

[10]The total useful energy time series, for the Greek energy system, are available upon request.

4.2 Preliminary analysis

In order to identify the exact order of integration of the variables involved in our study, we implement a set of unit root and stationarity tests. More specifically, we apply the Augmented Dickey-Fuller (ADF) test, with and without a trend as well as the Generalized Least Squares detrending Dickey-Fuller (GLS-DF) test, with and without a trend as well. The rationale for the use of the GLS-DF test is rooted on the fact that it improves the power of the well established in the literature ADF test (Elliott et al., 1996). Panels A and B in Table 2 below, display the results of the unit root tests for the two variables of our study. Clearly, both variables appear to be integrated of order one, regardless of the inclusion of the time trend, provided that in every case, we fail to reject the null hypothesis in the levels. At the same time, the opposite is true, when the same tests are reapplied not this time in the levels of the series but in their first differences.

Table 2: ADF and GLS-DF unit root tests.

Panel $A-$ADF test				
	Level		First Difference	
Variable	no-trend	trend	no-trend	trend
	$t-$Stat.(k)	$t-$Stat.(k)	$t-$Stat.(k)	$t-$Stat.(k)
Y	$-1.47(0)$	$-1.67(3)$	$-4.61(0)^{***}$	$-4.74(0)^{***}$
E	$-0.16(0)$	$-2.14(0)$	$-6.84(0)^{***}$	$-6.74(0)^{***}$
Panel $B-$GLS$-$DF test				
Y	$0.68(3)$	$-2.00(3)$	$-4.65(0)^{***}$	$-4.80(0)^{***}$
E	$2.07(0)$	$-2.09(0)$	$-6.44(0)^{***}$	$-6.72(0)^{***}$

Notes: ADF stands for the Augmented Dickey-Fuller test. GLS-DF stands for the Generalized Least Squares detrending Dickey-Fuller test, k represents the selected lag-length. A practical concern was the selection of the appropriate lag-length for the auxiliary regression since an extensive lag-length leads to loss of power, while at the same time a limited lag-length gives rise to serial correlation rendering our test biased; therefore, the lag-length for the ADF test as well as for the GLS-DF test was selected based on the Schwarz information criterion with $k_{min} = 0$ and $k_{max} = 10$.To determine the maximum lag-length (k_{max}), we implemented Schwert's principle (Schwert, 1989), that is, $k_{max} = 12(n/100)^{0.25}$, with n to be the sample size. Finally, $*$, $**$ and $***$ denote rejection of the null hypothesis at the 10%, 5% and 1% significance level, respectively.

In addition to the above unit root tests, we implement two stationarity tests which are the standard KPSS test and the six different types of the non-parametric Bierens-Guo test (Bierens and Guo, 1993). The chief advantage of the Bierens-Guo tests is the substantial gain in the asymptotic power, attributed to the fact that the approximation of the error variance does not involve the implementation of the Newey-West estimator as is the case with other stationary tests (Gaffeo et al., 2005). The results presented in Panels A and B of Table 3, suggest that the order of integration implied from the stationarity tests is the same with that derived from the unit root tests. We can, therefore, safely treat both of our investigated series as I(1) variables.

Table 3: KPSS and Bierens-Guo (type 1 to type 6) stationarity tests

Panel A-KPSS test

Variable	Level		First Difference	
	no-trend	trend	no-trend	trend
	LM-Statistic	LM-Statistic	LM-Statistic	LM-Statistic
Y	0.89***	0.28***	0.25	0.18
E	0.90***	0.24***	0.06	0.06

Panel B-Bierens-Guo tests

	Variable (level)				Variable (First Difference)			
	Y	E	Y	E	Y	E	Y	E
Type1	37.43**	30.99**	–	–	1.51	1.24	–	–
Type2	48.50**	48.99**	–	–	1.51	1.24	–	–
Type3	93.26***	67.23***	–	–	1.54	1.25	–	–
Type4	31.45**	98.72***	–	–	1.53	1.25	–	–
Type5	–	–	38.69**	31.87**	–	–	0.82	0.18
Type6	–	–	11.85*	9.56*	–	–	2.03	0.86

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, while the spectral estimation method used is the Bartlett kernel. Bierens and Guo stationarity tests (Bierens and Guo, 1993) type 1 to type 4 test the null hypothesis of a stationarity, while type 5 and 6 test the null hypothesis of a stationarity around a time trend. Finally, $*$, $**$ and $***$ denote rejection of the null hypothesis at the 10%, 5% and 1% significance level, respectively.

Finally, to rule out the case of false identification of the order of integration, we tested for the existence of unit roots in the series at hand allowing this time for the presence of one structural break. As is well known, failure to account for a possible structural break may give rise to the so-called Perron phenomenon or the converse Perron phenomenon (Leybourne et al., 1998). For this reason, we implemented the Zivot and Andrews (1992) unit root test

(ZA, hereafter) which permits endogenous identification of a possible structural break in the data. The rationale of the ZA unit root test is similar to the well known tests that have been proposed by Banerjee et al. (1992) and Perron (1997). Under the null hypothesis the ZA test assumes the presence of a unit root, while the alternative hypothesis suggests stationarity around a structural break, which takes place at an unknown time. The results of the three alternative specifications of the ZA test, that is i) break in intercept (model A), ii) break in trend (model B) and iii) break in intercept and trend (model C), are analytically illustrated in Table 4. Clearly, for all models (A, B and C), the ZA test fails to reject the null hypothesis of a unit root, at all the conventional significance levels. Overall, the ZA test results corroborate the findings of the unit root and stationarity tests.

Table 4: Zivot-Andrews unit root test (with one structural Break).

Variable	model$A$	model$B$	model$C$
	t-Stat.(k)break	t-Stat.(k)break	t-Stat.(k)break
Y	−2.23(3)2001	−2.74(3)1998	−2.57(3)1992
E	−3.51(0)1996	−2.27(0)1986	−3.31(0)1980

Notes: The critical values for model A at the 1%, 5% and 10% significance level are −5.34, −4.93 and −4.58, respectively. The critical values for model B for the same significance levels are −4.80, −4.42 and −4.11, respectively. Finally, the respective critical values for model C (for the same significance levels) are −5.57, −5.08 and −4.82. All the above mentioned critical values 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.

Another issue related to the non-linear causality testing procedure is the presence of cointegration. In cases where a long-run relationship exists the use of the vector-error correction model (VECM) is of utmost importance to confer the occurrence of causality in the standard VAR system (Engle and Granger, 1987). In order to examine the existence of a long-run relationship we implement the Johansen (1995) cointegration approach. The cointegration rank test results for the Trace Statistic along with the associated 5% critical values and the related p-value are showed in Table 5. The results do not reject, at any conventional significance level, the null hypothesis of zero cointegrating relationships. Hence, the Johansen cointegration approach, based on the Trace test, does not indicate the presence of a long-run relationship.

Table 5: The Johansen cointegration test.

Null hypothesis	Alternative	Trace Statistic	5% critical value	p-value
$r=0$	$r=1$	12.61	15.49	0.13
$r\leq 1$	$r=2$	0.12	3.84	0.73

Notes: The analysis is based on a VAR with a constant term and one lag for the endogenous variables. Similar is the cointegration inference when the Max-Eigen Statistic is used. Tests for serial correlation show no signs of misspecification.

5 Empirical results

Having completed our preliminary econometric analysis, we continue with the investigation of the presence of a linear causal relationship between the total useful energy series and economic growth we implement the standard Granger causality test (Granger, 1969). The standard Granger causality testing procedure given the lack of a cointegration relationship[11] necessitates the estimation of an unrestricted VAR model with the involved variables transformed in their fist differences. In order to ascertain the existence of a linear causality, running for example from energy to economic growth, our interest turns on the F-Statistic, which is obtained after testing the joint significance of the lagged energy values in explaining the current level of economic growth. The results in Table 6 show that total useful energy Granger causes economic growth at the 0.05 level of significance (F=6.480). However, based on the relevant value of the F-Statistic (F=0.654), no significant causality has been ascertained for the opposite direction. Overall, linear causality testing provides evidence in favor of a unidirectional causality running from energy to economic activity. In other words, and within a linear causality framework the results lend overwhelming support to the growth hypothesis and are consistent with the findings of Tsani (2010).

As the focus of our analysis is on the identification of a non-linear causality, we implement a simple non-linear dependence test, widely known as the BDS test, proposed by Brock et al. (1996). The BDS test assesses the validity of the i.i.d. assumption on the delinearized time series data. The delinearization of the series takes place within a standard bivariate VAR

[11]This implies that the Granger causality testing procedure may be performed without the need to estimate the associated error-correction specification.

Table 6: The standard Granger causality test.

Null Hypothesis examined	VAR lag length	$F-$Statistic	$p-$value
Y does not Granger cause E	1.000	0.654	0.422
E does not Granger cause Y	1.000	6.480**	0.014

Notes: $*$, $**$ and $***$ denote rejection of the null hypothesis at the 10%, 5% and 1% significance level, respectively. The VAR lag order was selected on the basis of the Akaike information criterion. The selected VAR lag order is equal to one. Summary of the causality inference: $E \rightarrow Y$ and $Y \nrightarrow E$.

framework. Table 7 below displays the BDS testing results corresponding to the residuals (for the energy equation) that come from an unrestricted VAR specification. Clearly, and irrespectively of the implemented dimension, the i.i.d. assumption is rejected even at the 0.01 significance level. Such a result signifies that non-linear causality testing procedures are those that are suitable to our case.

Table 7: The BDS test.

Dimension	BDS$-$Statistic	Std. error	$Z-$Statistic	$p-$value
2	0.048	0.011	4.401***	0.000
3	0.084	0.017	4.715***	0.000
4	0.117	0.021	5.450***	0.000
5	0.128	0.023	5.647***	0.000
6	0.135	0.022	6.040***	0.000

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

To carry out a causality testing within a non-linear context, the analysis proceeds with the implementation of two non-linear in nature causality tests. The first and the most commonly used test for this purpose is the non-parametric Hiemstra and Jones (1994) test, while the second and not so frequently used but nevertheless important test is the one proposed by Diks and Panchenko (2006). The major advantage of the Diks and Panchenko (2006) test over the Hiemstra and Jones (1994) one is that it corrects for the observed severe over-rejection of the null hypothesis, when this is actually true.

The hypothesis testing for the detection of non-linear causal linkages between the variables at hand is carried out in two sequential steps. In the first step both non-linear causality tests are applied directly on the raw differenced series, while in the second step both non-

Table 8: Non-parametric causality tests.

lx=ly	GDP → Total useful energy		Total useful energy→GDP	
	H.J.($p-$value)	D.P.($p-$value)	H.J.($p-$value)	D.P.($p-$value)
Panel A:Without filtering				
1	1.42*(0.07)	1.46*(0.07)	1.46* (0.07)	1.49* (0.07)
2	1.17 (0.12)	1.16 (0.12)	1.65**(0.04)	1.38* (0.08)
3	0.03 (0.48)	0.19 (0.42)	1.99**(0.02)	1.81**(0.03)
4	0.25 (0.40)	0.33 (0.37)	1.97**(0.02)	1.41* (0.08)
5	1.29*(0.09)	1.33*(0.09)	1.90**(0.02)	1.71**(0.04)
Panel B:With VAR filtering				
1	1.43 (0.08)	1.50*(0.06)	1.54* (0.06)	1.72**(0.04)
2	1.01 (0.16)	1.23 (0.11)	1.29* (0.09)	1.04 (0.15)
3	−0.73 (0.77)	−0.25 (0.60)	1.62* (0.05)	1.39* (0.08)
4	−0.03 (0.51)	0.18 (0.42)	1.61* (0.05)	1.22 (0.11)
5	0.77 (0.22)	1.16 (0.12)	1.74**(0.03)	1.67**(0.05)

Notes: $*$, $**$ and $***$ denote rejection of the null hypothesis at the 10%, 5% and 1% significance level, respectively. The VAR lag-order was selected based on the Akaike information criterion. The selected VAR lag-order is equal to one. H.J. refers to Hiemstra and Jones (1994) test while D.P. refers to the Diks and Panchenko (2006) test. Summary of the causality inference: $E \rightarrow Y$ and $Y \nrightarrow E$.

linear causality tests are repeated on the delinearized raw differenced series. As was the case with the BDS test the delinearization process takes place within a bivariate VAR model. This second step is considered of essential importance in order to ensure that any identified causality is solely non-linear in nature. The detailed results from the first step of the non-parametric causality tests are displayed in panel A of Table 8, whereas in panel B are displayed the results from the second step. Starting from the raw differenced series, we observe that the null hypothesis of no non-linear causality running from economic growth to total useful energy is rarely rejected for both implemented tests (the results are displayed in the first two columns in Panel A). Actually both tests provide fully matched results, according to which sporadic rejections of the null hypothesis occurs only for the first and the fifth lag length and not in a lower than the 0.1 level of significance. Turning now to the delinearized series, and under the same null hypothesis, presented in the first two columns in Panel B, the previously identified evidence of causality which has been characterized as sporadic now seems to have been spirited away. More specifically, the null hypothesis is rejected at the 0.1

significance level only for the Diks and Panchenko (2006) test and exclusively for the first lag length. Overall, the observed rejections of the null hypothesis, no matter whether the time series data are delinearized or not, do not lend support to the hypothesis of a systematic and consistent causal relationship.

Examining the null hypothesis of the opposite direction now, no non-linear causality is running from total useful energy to economic growth, there is sufficient statistical evidence in favor of rejecting the null hypothesis. In particular, regarding the raw differenced series the Hiemstra and Jones (1994) test rejects consistently the null hypothesis at the 0.05 significance level for the various selected lag-lengths, with the only exception to be the first lag-length, where the rejection arises at the 0.1 significance level (see the third column in Panel A). In similar fashion, the Diks and Panchenko (2006) test systematically rejects the null hypothesis but not always at the 0.05 significance level as the Hiemstra and Jones (1994) test does. Specifically, the null hypothesis is rejected at the 0.05 significance level for the third and the fifth lag while the rejection level rises at the 0.1 when the lag-length was set equal to 1, 2 and 4 (see the fourth column in Panel A). Finally, for the delinearized series and under the same null hypothesis, the two non-linear and non-parametric causality tests provide adequate evidence towards the rejection of the null hypothesis. The third column in panel B shows that the Hiemstra and Jones (1994) test rejects consistently the null hypothesis at the 0.1 significance level for the different implemented lag-lengths, with the only exception to occur in the final lag, where the rejection is at the 0.05 significance level. Similar is the causality inference when the Diks and Panchenko (2006) test is performed. Despite the removal of any linear component for both series, the null hypothesis is still rejected at the 0.05 significance level, when the lag-lengths were set equal to 1, and 5, while the rejection level rises at the 0.1 when the lag-length was equal to 3. The only two

cases where we fail to reject the null hypothesis for the conventional significance levels are when the lag-lengths took on the values 2 and 4. On the whole, based on the empirical results provided by the standard Granger causality test and the two non-linear and non parametric causality tests which are presented in Tables 6 and 8, it can be argued that for the case of Greece there is reasonable statistical evidence to support the growth hypothesis.

6 Conclusions

This article has examined the linear and non-linear causal linkages between total useful energy use and economic growth in the Greek economy. Given that energy flows comprise various and distinct qualities, our study makes an effort to account for these qualitative differences and in so doing to provide bias free energy time series data which are appropriate for the statistical investigation. Another novelty of our study is the adoption of a non-parametric and non-linear econometric framework in order to assess the causal linkage between economic growth and energy consumption. In particular, apart from the implementation of the standard Granger causality test (Granger, 1969); we applied the well known non-parametric Hiemstra and Jones (1994) test for non-linear causality as well as its recent modification, proposed by Diks and Panchenko (2006). Our final results for the Greek economy imply that there is reasonable statistical evidence to support the existence of a unidirectional causal relationship which occurs from energy consumption to economic growth.

With respect to policy implications, our non-linear causality tests yielded results suggesting that energy is a limiting factor to economic growth and the later is what is needed for a depression-ridden country such as Greece at this time, with the unemployment rate well above 18 percent threatening the cohesion of the entire Greek society. For example, sudden supply disruptions (*e.g.* due to dilapidated and insufficient public infrastructure) or increases in fuel prices (due to heavy taxation) for the purposes of maximization of government revenues may retard the current and damage the potential for future economic growth. Although our empirical findings lend overwhelming support to the growth hypothesis, nevertheless extreme caution should be applied in using these results to propose concrete economic policy measures to conserving energy. On the other hand, our findings should not be interpreted to mean that they necessarily oppose to all energy conservation policies, but rather to argue that well designed and carefully targeted energy conservation policies are expected to promote rather than to harm economic growth. For instance, lower energy use due to lower energy intensity because of a shift from heavy industry to high quality services could stimulate overall economic growth. It goes without saying that the right mix of energy inputs is of extreme importance in the design of an effective energy policy as the environmental concerns and also the penalties imposed from the violations of the Kyoto protocol (ratified by Greece in 2002) become increasingly important. Therefore, the shift to more efficient and, at the same time, less polluting energy forms is definitely a viable policy towards economic growth. Such growing concerns can be better served, when one combines qualitative adjusted data for the total energy consumption and quantifies the various parameters of the investigation with more advanced and reliable econometric techniques.

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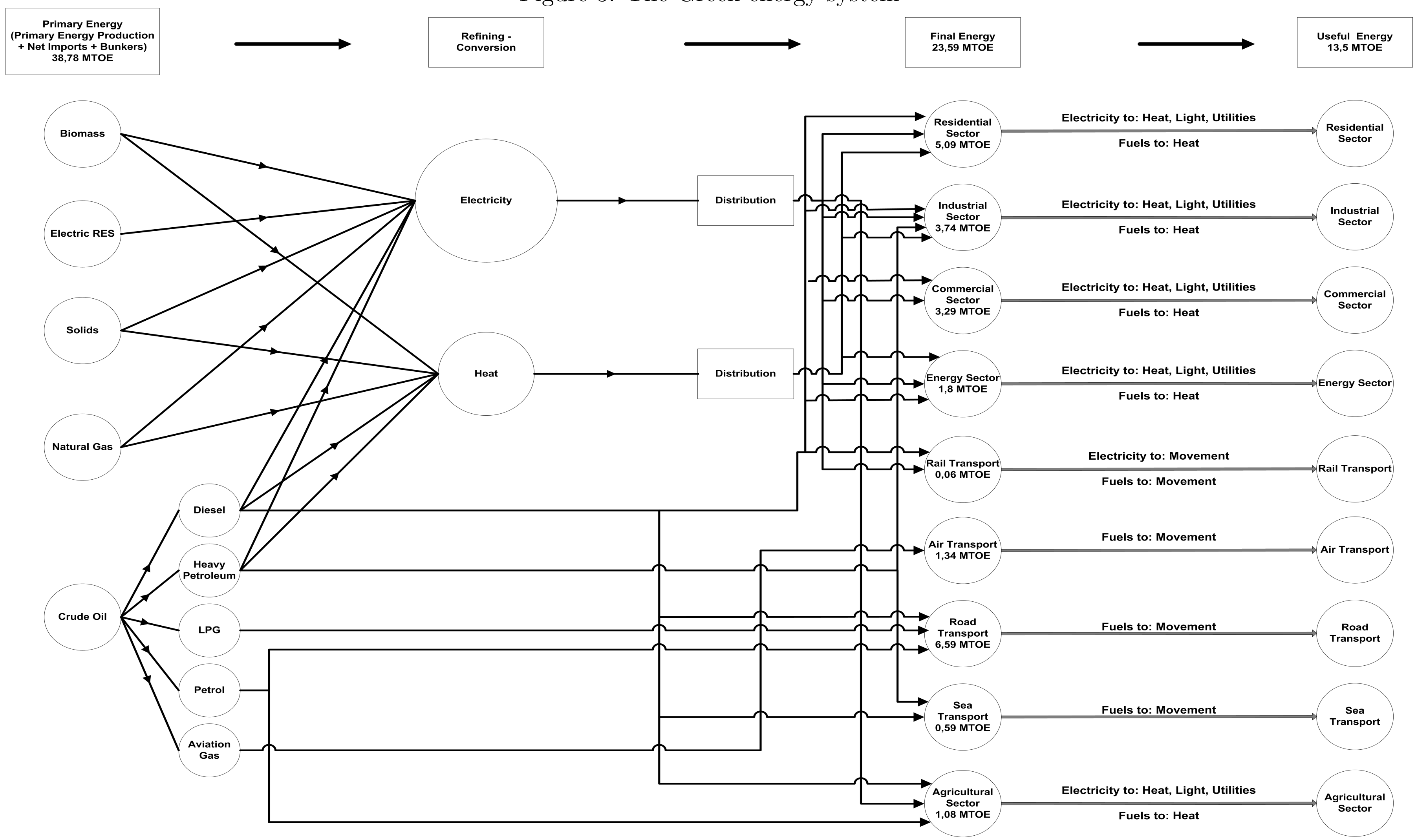
Appendix

Figure 3 below illustrates the topology of the Greek energy system which has been used in order to construct the time series of the total useful energy. The aggregate energy quantities (primary, final and useful) of the network refer for illustrative purposes only, to the last year of our study (2008). In the presented network all the different efficiencies associated with the transformation of the various energy forms into useful energy (*e.g.* heat, lighting, utilities or movement) have been considered. More specifically, after taking into account the primary energy production, the amount of net imports and finally, the contribution of the bunkers, energy enters into the Greek energy system (38.78 Mtoe) into various forms.The transformation of various energy forms into final useful energy goes through distinct stages. In the first stage, called refining-conversion stage, a fragment of the various primary energy forms is transformed into secondary energy (*e.g.* heat, electricity or oil derivatives).[12] At the second stage and via the network's distribution channels the secondary energy reaches as final energy (23.59 Mtoe) to the various segments of the economy for consumption. Finally, in the third stage, each economic segment, according to its end-use activities, utilizes a variety of equipment in order to convert final energy into useful energy (13.50 Mtoe).

Within the third stage, the relevant to the case efficient factors are utilized in order to approximate the amount of total useful energy for a given year. Therefore, the energy quality is delineated in terms of actual useful work. In order to extent the time series data of the total useful energy for the entire sample, the same process has been re-applied for every single year of the sample. By way of an example, let us focus on the agricultural segment for the entire sample period, where the following are the main sources of energy: electricity, lignite, petrol, diesel and heavy oil. From 1969 onwards, all transportations for agricultural purposes have been set aside and the transformed energy is restricted to pumping for irrigation purposes. Average efficiency for internal combustion engines running on petrol has been assumed to lie within the range of 30 to 32 percent, on diesel or heavy oil in the range of 40 to 42 percent and finally, for the electric engines the average efficiency is assumed to remain constant at 90 percent. Apart from engine efficiency, pumping efficiency has also been taken into account (average efficiency 78 to 80 percent). For the whole period under investigation the estimated efficiency in the agricultural sector ranges, depending on the year, between 28 to 41 percent. For the electricity consumption, the assumption which has been made for each economic sector is that it mainly serves the following three load types: thermal loads, lighting loads and loads related to other utilities. The share of each load varies depending on the economic sector and the time period. The last stage of Figure 3 portrays the total useful energy of each sector of the economy and summing them up we end up with a figure of the total useful energy measured in Mtoe for the Greek economy in each of the 48 years of study.

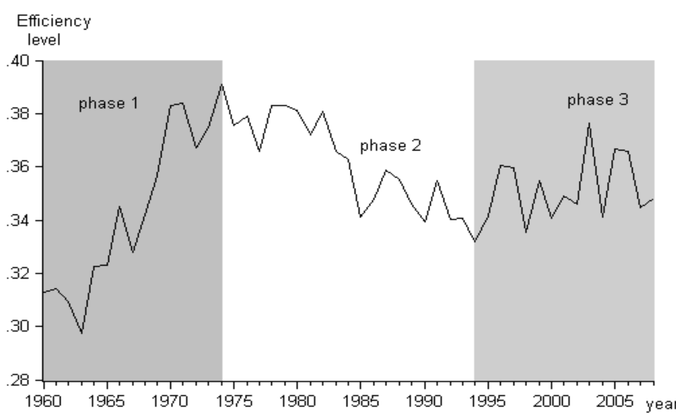
[12] Among the produced oil derivatives, diesel and heavy petroleum are also inputs used for the production of heat and electricity.

Figure 3: The Greek energy system



Most empirical studies concentrate on the use of primary energy, that is the energy prior to its transformation to other end-use energy forms, and in doing so disregard the qualitative differences among the various energy flows during the aggregation process. In short, these studies may suffer from aggregation bias, because as we find in our study of the Greek energy data the divergence between total primary energy and total useful energy is substantial. Figure 4 illustrates the overall efficiency of the Greek energy system defined by the ratio of the total useful energy to the total primary energy. We observe that the evolution of energy efficiency in Greece displays three distinct phases. The first phase, starting from 1964 and ending in 1974, is characterized by a rapidly rising trend and signifies the process of electrification of the country (along with the inherent improved conversion rates). The next two decades show a falling tendency efficiency which can be attributed to the growth of the transportation sector and the resulting increase in the use of diesel and petrol. This decrease has been reinforced by the greater share of lignite in the production of electricity. Finally, the integration of the natural gas in the Greek energy system by the mid 1990's resulted to the mild increase in the overall efficiency level at the 35 percent.

Figure 4: Efficiency of the Greek energy system



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