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The Frequency Domain Causality analysis between Energy Consumption and Income in the United States

Abstract

We investigated Granger-causality in the frequency domain between primary energy consumption / electricity consumption and GDP for the US by employing approach of Lemmens et al. (2008) and covering the period of January, 1973 to December, 2008. We find that causal and reverse causal relations between primary energy consumption and GDP and electricity consumption and GDP vary across frequencies. Our unique contribution in the existing literature lies in decomposing the causality on the basis of time horizons and demonstrating bidirectional the short-run, the medium-run and the long-run causality between GDP and primary energy consumption/electricity consumption and thus providing evidence for the feedback hypothesis. These results have important implications for the US for planning of the short-, the medium- and the long- run energy and economic growth related policies.

Key Words: energy consumption, economic growth, Granger-causality in the frequency domain
JEL Classification: Q40, Q43, Q53, Q56

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1. Introduction

Voluminous studies have examined the relationship between energy consumption and economic growth and suggested policy implications derived from their empirical findings. This line of inquiry stems basically, from the earlier oil shocks of the 1970s to the more recent interest on energy prices and the impact of the Kyoto protocol agreement by a number of industrialized and developing countries to conserve energy and reduce greenhouse emissions in face of achieving high growth rate of the economies. Economic theories, although, provide unambiguous relationship between energy consumption, and economic growth (see, section 2), empirical investigation of the relationship between these variables has been one of the most attractive areas of energy economics literature for the last two decades. In recent years, there has been a renewed interest in examining the relationship between these variables. The high economic growth rates experienced by developing countries are achievable only with the consumption of a larger quantity of commercial energy, which is one of the key factors of production, though it leads to environmental degradation. There is still dispute on whether energy consumption is a stimulating factor for, or a result of, economic growth. We in this study reinvestigate the same issue but used a recent frequency domain approach developed in Lemmens et al. (2008) and thus made a novel contribution to the research over the existing literature examining the relationship between energy consumption and economic growth. Our results have supported the findings of Yang (2000) for Taiwan, Zachariadis and Pashourtidou (2007) for Cyprus, Tang (2008) and Lean and Smyth (2010) for Malaysia, Aktas and Yilmaz (2008) for Turkey, Odhiambo (2009a) for South Africa, Lorde et al. (2010) for Barbados, Ouédraogo (2010) for Burkina Faso, Tiwari (2010) for India and Shahbaz et al. (2011) for Portugal.

We focus on the United States (US) because of the important role that it plays in world energy markets. Soytas et al. (2007) mentions few arguments in this regard. 'First, according to the Statistical Abstract of the US (2006), GHG emissions in the US rose nearly 17% between 1990 and 2000 before leveling off in 2001 and 2002. Second, over that same time period, the US accounted for around 23 to 24% of the world's total CO_2 emissions from consumption of fossil fuels. Third, the US share of total world energy production has fallen slightly from 20% in 1990 to 18% and 17% in the years 2000 and 2003, respectively. Fourth, over the same time frame, the US share of total world energy consumption has remained fairly constant at around 24%'. These, facts confirm that the US is a significant consumer, as well as producer, of energy in the world economy. Therefore, it is important to better understand the relationships that exist between the US economic growth and energy use before effective polices can be developed.

The issue of the possible impact of CO_2 emissions reduction on economic growth inevitably arises due to the possible connection between CO_2 emissions and energy consumption, and energy consumption and economic growth. Due to the importance of the possible connection between energy consumption and economic growth, there is a growing literature in this area. In general, studies find evidence of correlation between these two variables for countries with different economic structure and at different stages of economic development. The pioneering attempt in this area i.e., to study on the bi-directional relationships was made by Kraft and Kraft in the year of 1978. They applied the Granger-causality (GC) test to US data for the period of 1947-1974, and found that a unidirectional causality runs from economic growth to energy consumption, thus suggesting that an energy conservation policy is feasible. Since Kraft and Kraft (1978), there has been a vast body of studies contributing to this literature. Table 1 summarizes related studies.

Our observation from Table 1 indicates that studies in this area have yield mixed and often conflicting results for both developed and developing countries due to different methods, sample periods, and model specifications being employed. Furthermore, it is worth noting that most previous studies are limited in scope to the applications of linear models. However, economic events and regime changes such as changes in economic environment, changes in energy policy and fluctuations in energy price can cause structure changes in the pattern of energy consumption for a given time period under study. This creates a room for a nonlinear rather than linear relationship between energy consumption and economic growth. Therefore, in the present study we made an attempt to analyze the issue in **a** nonlinear framework by using a recently developed nonparametric approach of Lemmens et al. (2008). Use of this approach allows us to decompose the GC in the frequency domain. In frequency domain, the key idea is that a stationary process can be described as a weighted sum of sinusoidal components with a certain frequency λ. As a result, one can analyze these frequency components separately. This analysis will make it possible to determine whether the predictive power is concentrated at the quickly fluctuating components or at the slowly fluctuating components. As such, instead of computing a single GC measure for the entire relationship, the GC is calculated for each individual frequency component separately. Thus, the strength and/or direction of the GC can be different for each frequency. We in the present study have considered two measures of energy consumption namely, primary energy consumption and electricity consumption. Two measures of energy consumption have been used to see the robustness of our results. To the best of our knowledge, the analyses of GC from primary energy consumption and/or electricity consumption to economic growth and vice-versa have not yet been explored in the frequency domain.[1]

Table 1: Summary of Literature on Relationship between Electricity Consumption and Economic Growth

Authors	Time Period	Methodology	Variables	Cointegration	Findings (country studied)
Single-Country Studies					
Yang (2000)	1954-1997	GC	Real GDP and Electricity Consumption	No	EC $\leftrightarrow$ Y (Taiwan)
Aqeel and Butt (2001)	1955-1996	GC by Hsiao	Real GDP and Electricity Consumption	No	EC $\rightarrow$ Y(Pakistan)

[1] It is important to mention that our analysis is based on bivariate Granger causality analysis model and therefore, it suffers from the problem of omitted variable bias. However, we would like to argue that even if this is the case first, to the best of our knowledge there is no such test developed which analysis nonlinear Granger-causality in multivariate framework (the only exception is Breitung and Candelon (2006) which can be applied for the, at most, trivariate model however, here we have preferred test suggested by Lemmens et al. (2008) which has relatively more power vis-à-vis Breitung and Candelon's (2006) proposed test). Second, since the approach used in the study is based on nonlinear framework, we argue that if any omitted variable are able to transmit their effect on the measured variable and create nonlinearity in the data series, we are able to take care of the effect of those variables in our analysis through the approach we used.

Ghosh (2002)	1950-1997	JML, GC	Electricity Supply, Employment and Real GDP	Yes	ES ← Y(India)
Jumbe (2004)	1970-1999	GC,	Real GDP and Electricity Consumption	Yes	EC ← Y(Malawi)
Shiu and Lam (2004)	1971-2000	JML, VECM	Real GDP and Electricity Consumption	Yes	EC → Y(China)
Lee and Chang (2005)	1954-2003	JML, VECM	Real GDP per Capita and Electricity Consumption per Capita	Yes	EC → Y(Taiwan)
Narayan and Smyth (2005)	1966-1999	ARDL, VECM	Real GDP per Capita, Electricity Consumption per Capita and Employment	Yes	EC ← Y(Australia)
Yoo (2005)	1970-2002	JML, VECM	Real GDP and Electricity Consumption	Yes	EC → Y(Korea)
Yoo and Kim (2006)	1971-2002	JML, GC by Hsiao	Real GDP and Electricity Supply	No	ES ← Y(Indonesia)
Ho and Siu (2007)	1966-2002	JML, VECM	Real GDP and Electricity Consumption	Yes	EC → Y(Hong Kong)
Altinay and Karagol (2005)	1950-2005	GCDL	Real GDP and Electricity Consumption	N.A	EC → Y(Turkey)
Yusof and Latif (2007)	1980-2006	MJL, GC	Real GDP and Electricity Consumption	Yes	$EC \nLeftrightarrow Y$ (Malaysia)
Yaun et al. (2007)	1978-2004	JML, VECM	Real GDP and Electricity Consumption	Yes	EC → Y(China)
Mozumder and Marathe (2007)	1971-1999	JML, VECM	Real GDP per Capita, Electricity Consumption per Capita	Yes	EC ← Y(Bangladesh)
Narayan and Singh (2007)	1971-2002	ARDL, VECM	Real GDP, Electricity Consumption and Labor	Yes	EC → Y(Fiji Islands)
Zachariadis and Pashourtidou (2007)	1960-2004	JML, VECM, VARGFEVD	Real Income per Capita, Electricity Consumption, prices and weather	Yes	EC ↔ Y(Cyprus)
Tang (2008)	1972-2003	ARDL, TYDL	Gross National Product and Electricity Consumption	No	EC ↔ Y(Malaysia)
Aktas and Yilmaz (2008)	1970-2004	JML, VECM	Gross National Product and Electricity Consumption	No	EC ↔ Y(Turkey)
Abosedra et al. (2009)	1995-2005	MJL, GC, VARGFEVD	Real GDP, Electricity Consumption, Real Imports, Temperature and humidity	No	EC → Y(Lebanon)
Odhiambo (2009a)	1971-2006	JML, VECM	Real GDP per Capita and Electricity Consumption per Capita, Employment	Yes	EC ↔ Y(South Africa)
Odhiambo (2009b)	1971-2006	ARDL, VECM	Real GDP per Capita and Electricity Consumption per Capita	Yes	EC → Y(Tanzania)
Lean and Smyth (2010)	1971-2006	TYDL	Real GDP, Electricity Consumption, Exports, Capita and Labor	Yes	EC ↔ Y(Malaysia)
Ciarreta and Zarraga (2010)	1971-2005	TYDL	Real GDP and Electricity Consumption	N.A	EC ← Y (Spain)
Lorde et al. (2010)	1960-	JML, VECM	Real GDP, Electricity Consumption,	Yes	EC ↔

	2004		Capital, Labor and Technology		Y(Barbados)
Acaravci (2010)	1968-2005	JML, VECM	Real GDP and Electricity Consumption	Existed	EC → Y(Turkey)
Chandran et al. (2010)	1971-2003	ARDL, VECM	Electricity consumption, Real GDP and Prices	Yes	EC → Y(Malaysia)
Jamil and Ahmad (2010)	1960-2008	JML, VECM, VARGFEVD	Industrial Production, Electricity Consumption and Electricity Prices	Yes	EC ← Y(Pakistan)
Ouédraogo (2010)	1968-2003	ARDL, VECM	Real GDP, Electricity Consumption and Capital Formation	Yes	EC ↔ Y(Burkina Faso)
Tiwari (2010)	1971-2006	JJ, GC-TYDL	Electricity consumption and Employment	NA	EC ↔ Y(India)
Shahbaz et al. (2011)	1971-2009	ARDL, GC-VECM	Electricity consumption, economic growth, and employment	Yes	EC ↔ Y(Portugal)
Tiwari (2011a)	1971-2007	JJ, GC-VAR	Real GDP per capita, Electricity consumption, CO2 emissions, Labor and Capital	No	$EC \nleftrightarrow Y$ (India)
Tiwari (2011b)	1970-2007	VAR, GC-DL	Primary energy consumption, CO_2 emissions, and economic growth	No	EC ← Y(India)
Tiwari (2012)	1970-2005	Saikkonen and Lütkepohl's approach, GC-VAR	CO_2 emissions, energy consumption and economic growth.	No	$EC \nleftrightarrow Y$ (India)

Notes: Y and EC represent economic growth and electricity consumption. The uni-directional causality from economic growth to electricity consumption (electricity supply) is indicated by Y→ EC (ES), from electricity consumption to economic growth by EC → Y, bi-directional causality between electricity consumption and economic growth by EC ↔ Y and no causal relation between both variables by $EC \nleftrightarrow Y$. NA represents not applied. In methodology column EG, GC, VARGFEVD, JML, VECM, ARDL, PC, TYMWT, TYBSA, VAR and DL means respectively Engle and Granger, Granger causality, Vector Autoregression Generalized Forecast Error Variance Decomposition, Johansen's Maximum Likelihood, Vector Error Correction Method, Autoregressive Distributed Lag Model to Cointegration, Panel Cointegration, Toda and Yamamoto (1995) M-Wald causality test, Toda and Yamamoto Bootstrapping causality analysis, Vector Autoregressive causality test and Dolado and Lütkepohl (1996) causality analysis etc.

Source: Author's compilation

The next section discusses the hypothesis data source and methodology. Section three presents empirical findings and section four draws conclusions and policy implications.

2. Hypotheses, Data Source and Methodology

The direction of causality between the energy consumption and economic growth has important policy implications as energy conservation policy may or may not be adopted, depends on the direction of causality. Unidirectional causality running from GDP to energy consumption (EC) implies that income is the initial receptor of exogenous shocks and equilibrium is restored through adjustment in EC. These are less energy dependent economies and energy conservation policies may be implemented without adverse effects on economic growth and employment. On the other hand, if causality runs from EC to GDP then it implies that the economy is energy dependent and EC measures may stimulate economic growth. Bidirectional causality indicates that both EC and high level of economic activity mutually persuade each other. Finally, no-causality between EC and economic growth referred as "neutrality hypothesis" implies that energy conservation measure may pursued without affecting the economy.

For the analysis we obtain data of primary energy consumption and electricity consumption from the US Energy Information Administration (June 2011 Monthly Energy Review) with monthly observations. Data of real GDP is obtained from http://www.bea.doc.gov/ with annual observations. In order to match the observations GDP data is interpolated using **a** linear interpolation method however, results are unaffected significantly if cubic interpolation is used. Our study period is January, 1973 to December, 2008.[2]

Analysing time series in frequency domain i.e., spectral analysis could be helpful in supplementing the information obtained by time-domain analysis (Granger 1969) and Priestley 1981). Spectral analysis highlights the cyclical properties of data. In our study, we follow the bivariate GC test over the spectrum proposed by Lemmens et al. (2008). They have reconsidered the original framework proposed by Pierce (1979), and proposed a testing procedure for Pierce's spectral GC measure. This GC test in the frequency domain relies on a modified version of the coefficient of coherence, which they estimate in a nonparametric fashion, and for which they derive the distributional properties.

Let E_t and Y_t be two stationary time series of length T representing Energy/Electricity consumption and Output/GDP respectively. The goal is to test whether E_t Granger cause Y_t at a given frequency λ. Pierce's measure for GC (Pierce 1979) in the frequency domain is performed on the univariate innovations series, u_t and v_t, derived from filtering the E_t and Y_t as univariate ARMA processes, i.e.

$$\Theta^E(L)E_t = C^E + \Phi^E(L)\varsigma_t \tag{1}$$

$$\Theta^y(L)Y_t = C^y + \Phi^y(L)\xi_t \tag{2}$$

where $\Theta^E(L)$ and $\Theta^y(L)$ are autoregressive polynomials, $\Phi^E(L)$ and $\Phi^y(L)$ are moving average polynomials and C^E and C^y potential deterministic components. The obtained innovation series ς_t and ξ_t, which are white-noise processes with zero mean, possibly correlated with each other at different leads and lags. The innovation series ς_t and ξ_t, are the series of importance in the GC test proposed by Lemmens et al (2008).

[2] Here, we want to clear that we have preferred to interpolate GDP instead using industrial production data of which sufficient observations are available because first, interpolation of the data do not destroy the true property of the data (excepting some cases when an economy experiences abrupt changes so frequently); second, of course, industrial production is used in many studies as a proxy for GDP however, it is not true representative of the economies, particularly developed one where major contributor in GDP is the service sector. Finally we have relied on the results obtained from linear interpolation method as this method while changing the frequency to a higher one, maintains the sum, average or final value over each period of the levels which is not the case with other method such as Cubic interpolation. This interpolation was done in SAS software using "*proc expand*" command and keeping "observed=average" values and for cubic interpolation we used "*proc expand*" with "method=spline(natural)". For details on it one can refer to SAS procedures in details.

Let $S_{\varsigma}(\lambda)$ and $S_{\xi}(\lambda)$ be the spectral density functions, or spectra, of ς_t and ξ_t at frequency $\lambda \in]0,\pi[$, defined by

$$S_{\varsigma}(\lambda) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_{\varsigma}(k)e^{-i\lambda k} \quad (3)$$

$$S_{\xi}(\lambda) = \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_{\xi}(k)e^{-i\lambda k} \quad (4)$$

where $\gamma_{\varsigma}(k) = \text{Cov}(\varsigma_t, \varsigma_{t-k})$ and $\gamma_{\xi}(k) = \text{Cov}(\xi_t, \xi_{t-k})$ represent the autocovariances of ς_t and ξ_t at lag k. The idea of the spectral representation is that each time series may be decomposed into a sum of uncorrelated components, each related to a particular frequency λ.[3] The spectrum can be interpreted as a decomposition of the series variance by frequency. The portion of variance of the series occurring between any two frequencies is given by area under the spectrum between those two frequencies. In other words, the area under $S_{\varsigma}(\lambda)$ and $S_{\xi}(\lambda)$, between any two frequencies λ and $\lambda + d\lambda$, gives the portion of variance of ς_t and ξ_t respectively, due to cyclical components in the frequency band $(\lambda, \lambda + d\lambda)$.

The cross spectrum represents the cross covariogram of two series in frequency domain. It allows determining the relationship between two time series as a function of frequency. Let $S_{\varsigma\xi}(\lambda)$ be the cross spectrum between ς_t and ξ_t series. The cross spectrum is a complex number, defined as,

$$\begin{aligned} S_{\varsigma\xi}(\lambda) &= C_{\varsigma\xi}(\lambda) + iQ_{\varsigma\xi}(\lambda) \\ &= \frac{1}{2\pi}\sum_{k=-\infty}^{\infty}\gamma_{\varsigma\xi}(k)e^{-i\lambda k} \end{aligned} \quad (5)$$

where $C_{\varsigma\xi}(\lambda)$ is called cospectrum and $Q_{\varsigma\xi}(\lambda)$ is called quadrature spectrum are respectively, the real and imaginary parts of the cross-spectrum and $i = \sqrt{-1}$. Here $\gamma_{\varsigma\xi}(k) = \text{Cov}(\varsigma_t, \xi_{t-k})$ represents the cross-covariance of ς_t and ξ_t at lag k. The cospectrum $Q_{\varsigma\xi}(\lambda)$ between two series ς_t and ξ_t at frequency λ can be interpreted as the covariance between two series ς_t and ξ_t that is attributable to cycles with frequency λ. The quadrature spectrum looks for evidence of out-of-phase cycles (see Hamilton 1994, pp.274). The cross-spectrum can be estimated non-parametrically by,

$$\hat{S}_{\varsigma\xi}(\lambda) = \frac{1}{2\pi}\left\{\sum_{k=-M}^{M} w_k\,\hat{\gamma}_{\varsigma\xi}(k)e^{-i\lambda k}\right\} \quad (6)$$

[3] The frequencies λ_1, λ_2, ….., λ_N are specified as follows: $\lambda_1 = 2\pi/T$, $\lambda_2 = 4\pi/T$, …. The highest frequency considered is $\lambda_N = 2N\pi/T$; where $N \equiv T/2$, if T is an even number and $N \equiv (T-1)/2$, if T is an odd number (see Hamilton 1994, pp.159).

with $\hat{\gamma}_{\varsigma\xi}(k) = \hat{COV}(\varsigma_t, \xi_{t-k})$ the empirical cross-covariances, and with window weights w_k, for $k = -M,..., M$. Equation (6) is called the *weighted covariance estimator*, and the weights w_k are selected as, the Bartlett weighting scheme i.e. $1-|k|/M$. The constant M determines the maximum lag order considered. The spectra of Equation (3) and (4) are estimated in a similar way. This cross-spectrum allows us to compute the coefficient of coherence $h_{\varsigma\xi}(\lambda)$ defined as,

$$h_{\varsigma\xi}(\lambda) = \frac{|S_{\varsigma\xi}(\lambda)|}{\sqrt{S_{\varsigma}(\lambda)S_{\xi}(\lambda)}} \tag{7}$$

Coherence can be interpreted as the absolute value of a frequency specific correlation coefficient. The squared coefficient of coherence has an interpretation similar to the R-squared in a regression context. Coherence thus takes values between 0 and 1. Lemmens et al. (2008) have shown that, under the null hypothesis that $h_{\varsigma\xi}(\lambda) = 0$, the estimated squared coefficient of coherence at frequency λ, with $0 < \lambda < \pi$ when appropriately rescaled, converges to a chi-squared distribution with 2 degrees of freedom[4], denoted by χ^2_2.

$$2(n-1)\hat{h}^2_{\varsigma\xi}(\lambda) \xrightarrow{d} \chi^2_2 \tag{8}$$

where $\to^d$ stands for convergence in distribution, with $n = T/\left(\sum_{k=-M}^{M} w_k^2\right)$. The null hypothesis $h_{\varsigma\xi}(\lambda) = 0$ versus $h_{\varsigma\xi}(\lambda) > 0$ is then rejected if

$$\hat{h}_{\varsigma\xi}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n-1)}} \tag{9}$$

with $\chi^2_{2,1-\alpha}$ being the $1-\alpha$ quantile of the chi-squared distribution with 2 degrees of freedom. The coefficient of coherence in Equation (7) gives a measure of the strength of the linear association between two time series, frequency by frequency, but does not provide any information on the direction of the relationship between two processes. Lemmens et al. (2008) have decomposed the cross-spectrum (Equation 5) into three parts: (i) $S_{\varsigma\Leftrightarrow\xi}$, the instantaneous relationship between ς_t and ξ_t; (ii) $S_{\varsigma\Rightarrow\xi}$, the directional relationship between ς_t and lagged values of ξ_t; and (iii) $S_{\varsigma\Rightarrow\xi}$, the directional relationship between ξ_t and lagged values of ς_t, i.e.,

$$S_{\varsigma\xi}(\lambda) = [S_{\varsigma\Leftrightarrow\xi} + S_{\varsigma\Rightarrow\xi} + S_{\xi\Rightarrow\varsigma}]$$
$$= \frac{1}{2\pi}\left[\gamma_{\varsigma\xi}(0) + \sum_{k=-\infty}^{-1}\gamma_{\varsigma\xi}(k)e^{-i\lambda k} + \sum_{k=1}^{\infty}\gamma_{\varsigma\xi}(k)e^{-i\lambda k}\right] \tag{10}$$

[4] For the endpoints $\lambda = 0$ and $\lambda = \pi$, one only has one degree of freedom since the imaginary part of the spectral density estimates cancels out.

The proposed spectral measure of GC is based on the key property that ς_t does not Granger cause ξ_t if and only if $\gamma_{\varsigma\xi}(k) = 0$ for all $k < 0$. The goal is to test the predictive content of ς_t relative ξ_t to which is given by the second part of Equation (10), i.e.

$$S_{\varsigma\Rightarrow\xi}(\lambda) = \frac{1}{2\pi}\left[\sum_{k=-\infty}^{-1}\gamma_{\varsigma\xi}(k)e^{-i\lambda k}\right] \qquad (11)$$

The Granger coefficient of coherence is then given by,

$$h_{\varsigma\Rightarrow\xi}(\lambda) = \frac{|S_{\varsigma\Rightarrow\xi}(\lambda)|}{\sqrt{S_{\varsigma}(\lambda)S_{\xi}(\lambda)}} \qquad (12)$$

Therefore, in the absence of GC, $h_{\varsigma\Rightarrow\xi}(\lambda) = 0$ for every λ in $[0,\pi]$. The Granger coefficient of coherence takes values between zero and one, Pierce (1979). Granger coefficient of coherence at frequency λ is estimated by

$$\hat{h}_{\varsigma\Rightarrow\xi}(\lambda) = \frac{\left|\hat{S}_{\varsigma\Rightarrow\xi}(\lambda)\right|}{\sqrt{\hat{S}_{\varsigma}(\lambda)\hat{S}_{\xi}(\lambda)}}, \qquad (13)$$

with $\hat{S}_{\varsigma\Rightarrow\xi}(\lambda)$ as in Equation (6), but with all weights w_k =0 for $k \geq 0$. The distribution of the estimator of the Granger coefficient of coherence is derived from the distribution of the coefficient of coherence Equation (8). Under the null hypothesis $\hat{h}_{\varsigma\Rightarrow\xi}(\lambda) = 0$, the distribution of the squared estimated Granger coefficient of coherence at frequency λ, with $0 < \lambda < \pi$ is given by,

$$2(n'-1)\hat{h}^2_{\varsigma\xi}(\lambda) \xrightarrow{d} \chi^2_2 \qquad (14)$$

where n is now replaced by $n' = T/\left(\sum_{k=-M}^{-1} w_k^2\right)$. Since the w_k s', with a positive index k, are set equal to zero when computing $\hat{S}_{\varsigma\Rightarrow\xi}(\lambda)$, in effect only the w_k with negative indices are taken into account. The null hypothesis $\hat{h}_{\varsigma\Rightarrow\xi}(\lambda) = 0$ versus $\hat{h}_{\varsigma\Rightarrow\xi}(\lambda) > 0$ is then rejected if

$$\hat{h}_{\varsigma\Rightarrow\xi}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n'-1)}} \qquad (15)$$

Afterward, we compute Granger coefficient of coherence given be Equation (13) and test the significance of causality by making use of Equation (15).

3. Empirical Findings

First of all we tested for the stationarity of the variables considered in our study through Phillips and Perron (PP) (1988) test, Kwiatkowski et al. (KPSS) (1992) test and Zivot and Andrews (ZA) (1992) test.[5] We report results of unit root analysis in Table 1 below.

Insert Table 1 about here

It is evident from Table 1 that results obtained from PP and KPSS unit root tests are ambiguous hence we relied upon ZA unit root test as this test takes into account structural break in the data series. In the literature it has been well documented that the unit root test that do not take into account the structural breaks are potentially misleading. Our results of ZA test show that all variables are stationary in the level form i.e., they are integrated of order zero, I(0). Hence to proceed with, we used the log level form of the variables. Further, to analyze GC between primary energy consumption and GDP and electricity consumption and GDP we filtered all variables using ARMA models in order to obtain the innovation series. We have used lag length[6] $M = \sqrt{T}$. The frequency (λ) on the horizontal axis can be translated into a cycle or periodicity of T months by $T = 2\pi / \lambda$; where T is the period. Since, we have interpolated GDP annual data to the monthly frequencies, we compared the results of two different interpolation method to show that whether our interpolation approach matters in drawing conclusion or not.

Figure 1, which presents the result of Granger coefficient of coherence for causality running from GDP (in panel A and B) to primary energy consumption, shows that at 5% level of significance, GDP Granger-cause primary energy consumption at level of frequencies reflecting long-run, medium-run as well as short run business cycles. Further, both panel i.e., Panel A and panel B show that Granger-coefficient of coherence which is calculated at different frequencies is higher (and relatively much higher in panel A) to the critical value indicating that there is high strength of Granger-causality running from GDP to primary energy consumption. So, we find that our interpolation procedure has only affected the strength of Granger-causality not the direction and our overall conclusion.

Insert Figure 1 about here

Similarly, Figure 2, which presents the result of Granger coefficient of coherence for causality running from primary energy consumption to GDP (in panel A and B), shows that at 5% level of significance, primary energy consumption Granger-causes GDP at all the levels of frequencies reflecting short-run, medium-run and long-run cycles. Similar to Figure 1, Figure 2 also reports that Granger-coefficient of coherence at different frequencies is higher (and relatively much higher in panel A) to the critical value indicating that there is high strength of Granger-causality running from primary energy consumption to GDP. Here we note two points:-

[5] Time series plot and descriptive statistics of the variables are presented in Figure 1 and Table 1 respectively, in Appendix. Table 1 of appendix indicates that all the three variables do not have log normal distribution and therefore, provides scope for our nonlinear analysis. Results of unit root analysis are not presented for space consideration however; it can be obtained from the author upon request.

[6] Following Diebold (2001, pp.136) we take M equal to the square root of number of observations T.

a) as we move for higher frequencies we find that value of Granger-coefficient of coherence shows in general tendency to move up (of course this upward movement has cyclical movement; b) at very low level of frequency (or in the very long run) i.e., between 0-0.2 in panel B, we do not find evidence that primary energy consumption Granger-causes GDP.

Insert Figure 2 about here

Figure 3, which present the result of Granger coefficient of coherence for causality running from GDP (in panel A and B) to electricity consumption, shows that at 5% level of significance, GDP Granger-cause electricity consumption at all level of frequencies reflecting long-run, medium-run as well as short run business cycles. However, here we observe on difference in the diagrammatic results reported in panel A and panel B of Figure 3. In panel A we observe a clear evidence that GDP Granger-cause electricity consumption and in panel B we find that in the very short range of medium frequencies (i.e., between 1.6-1.8) we do not find that GDP Granger-causes electricity consumption. So, we find that our interpolation procedure in this case only has affected the strength as well as evidence of Granger-causality.

Insert Figure 3 about here

Figure 4 presents the result of Granger coefficient of coherence for causality running from electricity consumption to GDP (in panel A and panel B), shows that at 5% level of significance, electricity consumption Granger-causes GDP at all the frequencies. This reflects that electricity consumption Granger-causes GDP over the short-run, medium-run as well as long-run business cycles. In this case too, as with the previous cases, we find that choice of method employed for the interpolation of GDP has a little impact on the strength of the Granger-causality.

Insert Figure 4 about here

4. Conclusions

In the present study we analyzed GC from primary energy consumption and electricity consumption to GDP for the US by using monthly data covering the period of January, 1973 to December, 2009.

Our results show, for the US economy, that causal and reverse causal relations and its strength between energy consumption and real GDP and electricity consumption and real GDP vary across frequencies. Specifically, our results reveal that primary energy consumption and real GDP both Granger-causes each other in all the frequencies. Hence, we show that both primary energy consumption and high level of economic activity mutually persuade each other over the short-run, the medium-run and the long-run. With respect to the results of GC in the frequency domain between electricity consumption and real GDP are similar to those obtained for the GC between real GDP and primary energy consumption. Hence, we find that energy consumption (measured either as primary energy or electricity consumption) and real GDP

Granger-causes each other at low, intermediate and higher frequencies and thus provide support for the feedback hypothesis. Therefore, energy consumption (in general) and real GDP serve as complements to each other. Hence, in one hand energy conservation-oriented policies may have a detrimental impact of economic growth of the US, on the other to attain higher economic growth path may amplify the energy consumption. Thus US government while formulating the policies related to energy and economic growth should keep the bidirectional causal evidence in the mind. This is particularly because the feedback relationship between energy consumption and economic growth increases the effect of energy conservation on economic growth. Say for example when at the first place energy conservation policy is adopted then it will lead to the reduction of economic growth and then low level of economic growth causes the lower level of energy consumption and again economic growth decreases. Hence, the US economy should not follow energy conservation policy for total economy since it causes two opposite effects on the economy. However, the suggestive point is that the causal relationships between energy consumption and economic growth may be changed at the disaggregated level. Hence, while optimal energy policy may need conservation of energy consumption for some sectors or energy kinds, there may be no need for energy conservation policy for the others and thus optimal portfolio can be obtained in the utilization of various energy sectors or energy kinds.

The unique contribution of the present study lies in decomposing the causality on the basis of time horizons and demonstrating bidirectional the short-run, the medium-run and the long-run causality between the GDP and energy consumption, in general. We have also been able to demonstrate the cyclical nature of the causal relationship between our test variables. Finally, our study has also contributed by showing the strength of the Granger-causality.

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Figure 1: Granger causality from GDP to primary energy consumption. The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance

A	B

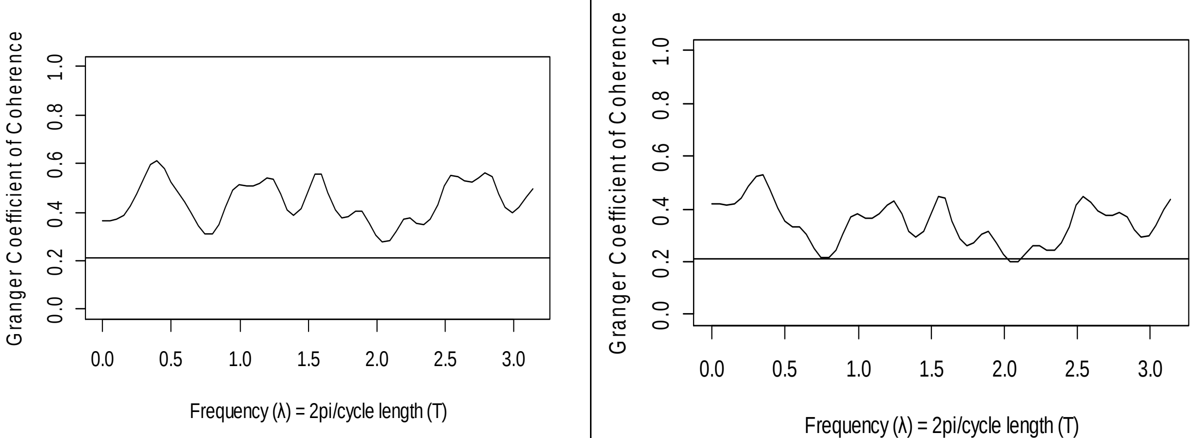


Figure 2: Granger causality from primary energy consumption to GDP. The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance

A	B

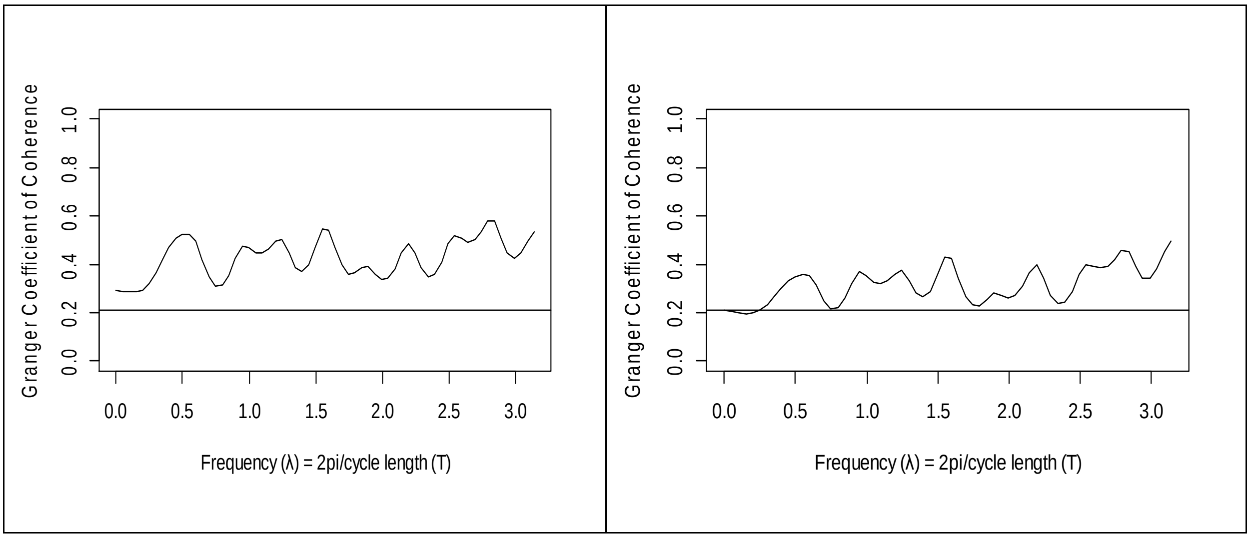


Figure 3: Granger causality from GDP to electricity consumption. The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance

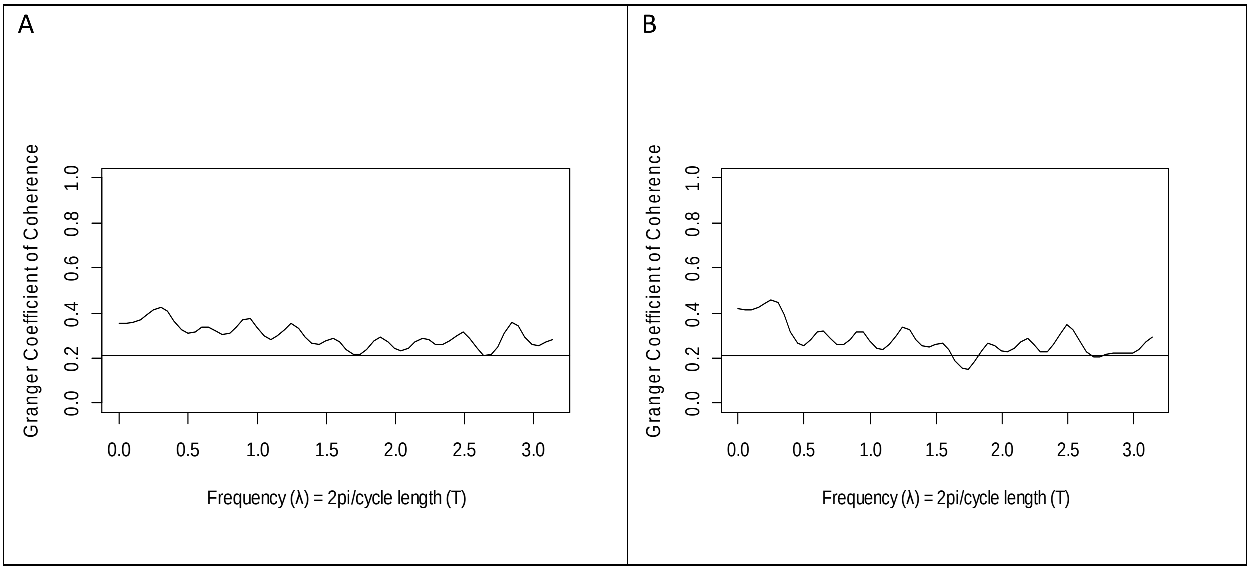


Figure 4: Granger causality from electricity consumption to GDP. The line parallel to the frequency axis represents the critical value for the null hypothesis, at the 5% level of significance

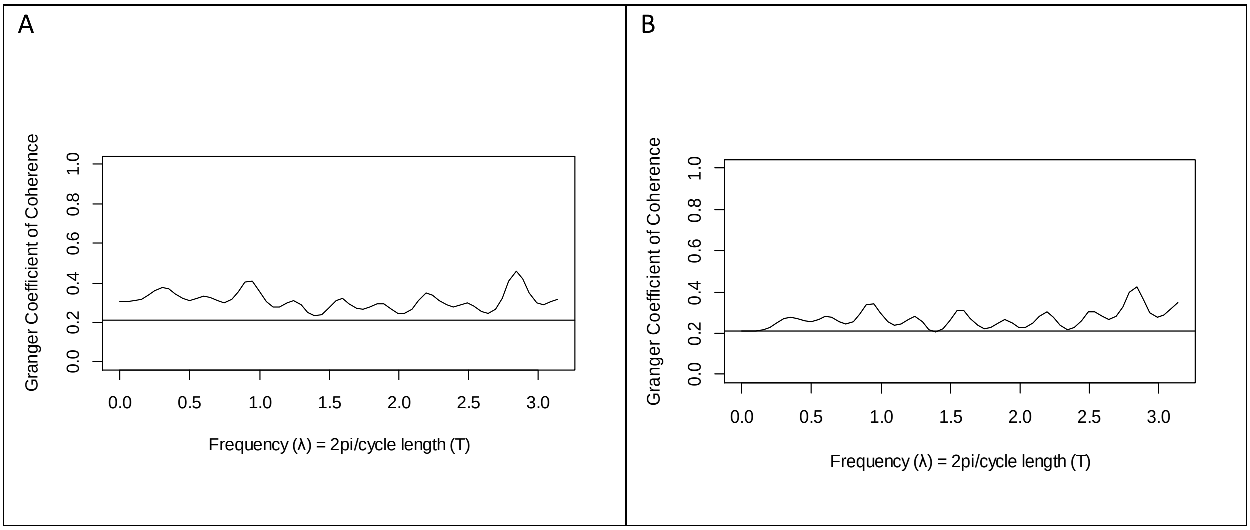


Table-1: PP, KPSS and ZA Unit Root Estimation

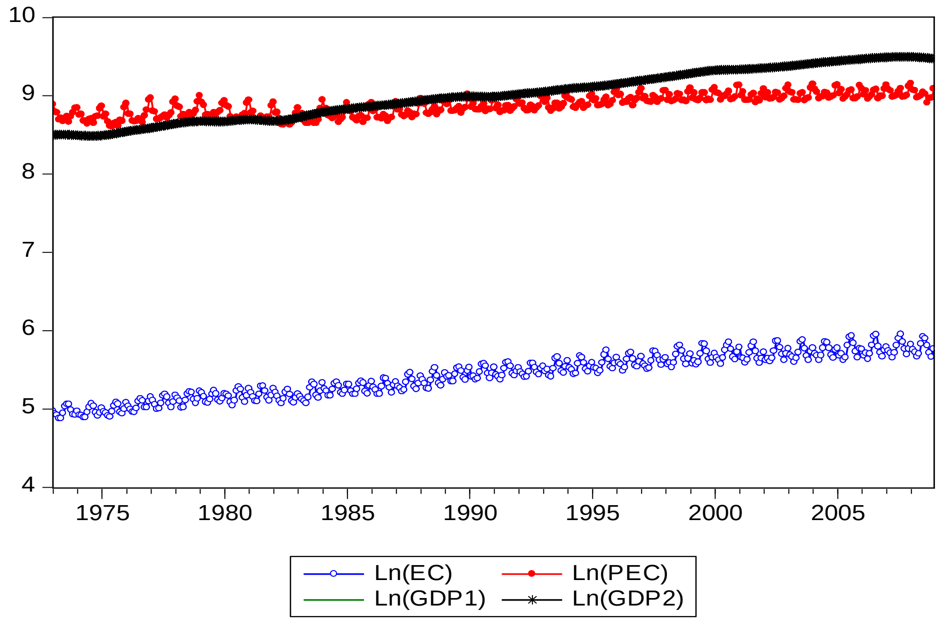
Unit root test: Constant and Linear Trend						
Variables	PP test		KPSS test		ZA test	
	t-statistic	Bandwidth	t-statistic	Bandwidth	t-statistic	Lag
Ln(EC)	-11.1901***	223	0.71280***	4	-7.45844*** (2001M01)	4
Ln(PEC)	-9.644338***	8	0.39281***	7	-11.6150*** (1981M02)	7
Ln(GDP1)	-2.600382	16	0.083132	16	-2.429232*** (1998M03)	16
Ln(GDP2)	-1.930318	16	0.090097	16	-2.973513*** (2002M04)	15
Note: (1) GDP1 is obtained using a linear interpolation method and GDP2 is obtained using a cubic interpolation. (2) ZA test-critical values at 1%, 5% and 10% significance level respectively are -5.57, -5.08, and -4.82 for model when breaks occur in intercept and trend both. (3) KPSS test-critical values are- 0.216, 0.146 and 0.119 respectively for 1%, 5% and 10% level of significance. (4) PP test-critical values are -3.979493, -3.420283 and -3.132811 respectively for 1%, 5% and 10% level of significance level. (5) We used Bandwidth: (Newey-West automatic) using Bartlett kernel.						

Appendix

Table 1: Discriptive statistics

	Ln(EC)	Ln(PEC)	Ln(GDP1)	Ln(GDP2)
Mean	5.419443	8.872031	8.995869	9.008425
Median	5.451600	8.877170	8.990502	8.991263
Maximum	5.953059	9.154431	9.498666	9.498123
Minimum	4.877949	8.601188	8.481248	8.487356
Std. Dev.	0.274354	0.131572	0.318821	0.318021
Skewness	-0.151128	-0.029806	0.007425	-0.015713
Kurtosis	1.876665	1.970762	1.737696	1.731145
Jarque-Bera (Probability)	24.35831 (0.000005)	19.13191 (0.000070)	28.68538 (0.000001)	28.99763 (0.000001)
Sum	2341.200	3832.717	3886.215	3891.640
Sum Sq. Dev.	32.44141	7.461121	43.80976	43.59022
Observations	432	432	432	432

Figure 1: Time series plots of the variables in logarithms form



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