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ARTICLE INFO	Alper Ozun and Atilla Cifter (2007). Multi-scale Causality Between Energy Consumption and GNP in Emerging Markets: Evidence from Turkey. *Investment Management and Financial Innovations*, *4*(2)
RELEASED ON	Saturday, 23 June 2007
JOURNAL	"Investment Management and Financial Innovations"
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

MULTI-SCALE CAUSALITY BETWEEN ENERGY CONSUMPTION AND GNP IN EMERGING MARKETS: EVIDENCE FROM TURKEY

Alper Ozun[*], Atilla Cifter[**]

Abstract

Tests results for causality between energy consumption and economic growth do not have a consensus in the financial economics literature. Empirical evidence varies on the economies examined and methodology employed. This paper proposes a wavelet analysis as a semi-parametric model for detecting multi-scale causality between electricity consumption and growth in emerging economies. Using wavelet analysis, we find that in the short run there is feedback relationship between GNP and energy consumption, while in the long run GNP leads to energy consumption. Wavelet correlation between GNP and energy consumption is maximum at 3rd time-scale (5-8 years) and this shows that GNP affects electricity consumption maximally around 5-8 years later in the long-run. We also find that the magnitude of the wavelet correlation changes based on time-scales for GNP and energy consumption and this indicates that GNP and energy consumption are fundamentally different in the long run.

Key Words: Economic Growth, Energy Consumption, Employment, Wavelets, Causality.
JEL classification: Q43, C32, C1.

1. Introduction

Energy is considered as a filtering factor for economic growth in some researches since production is negatively affected by lack of energy (Jumbe, 2004; Stern, 2000). In reverse, there exists evidence showing that economic growth is an energy consumption resource (Masih and Masih, 1996). According to Soytas and Sari (2006), the lack of consensus on the causality between energy and output might be because of the fact that the economies have different energy consumption patterns and various sources of energy. Therefore, different sources of energy might have varying impacts on the output of an economy.

Recent financial theory argues that a causal relationship should be expected between the two variables since energy is an important factor for both demand and supply sides of the economy. According to Chontanawat, Hunt and Pierse (2006), on the demand side, customers see energy as a product to maximise their utilities. On the supply side, energy is a crucial factor for production, economic growth and development. Whether the economic growth is a driving factor for energy consumption or vice versa should be investigated with taking into consideration a causal relationship as well. They test for causality between energy and GDP for 30 OECD and 78 non-OECD countries and find out that causality from aggregate energy consumption to GDP and GDP to energy consumption is more prevalent in the advanced OECD countries compared to the developing non-OECD countries. Those findings indicate that a policy to reduce energy consumption aimed at reducing emissions is likely to have greater impact on the GDP of the developed rather than the developing world.

This paper argues that apart from the economy under investigation, the methodology has also crucial effects on the degree and direction of the causality between energy consumption and growth. In emerging financial markets, the test results of financial/economics time series are mostly methodology dependent. In emerging markets, there exist non-linearities, regime switching and chaotic patterns in the financial variables. From that point of motivation, this article uses a recent meth-

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odology transformed from Physics to the financial economics, namely wavelets in order to reach stronger evidence among electricity consumption and growth in Turkey as an emerging market.

By employing the same data used by Soytas and Sari (2006) from Turkish manufacturing industry, this research seeks further and stronger evidence with Turkish economy. In that respect, the sample period and variables for the data set are fixed to see the methodological effects in the relationship. The methodological motivation behind the paper is that financial and economic time series in emerging markets should be analysed with advanced methodologies which do not relying on the normal distribution assumption restricting time series analysis in accurate level. Advanced models like neural networks, wavelets or wavelets networks are proper methodological solutions for analysing financial and economic time series without assuming normality in data distribution.

The article is constructed as follows. In the next part, a short literature review is presented without giving detail in theoretical background, which is examined in many theoretical or empirical papers on the issue. In the third part, data and variables are introduced with their descriptive statistics and unit root tests. In the same part, wavelet methodology used mostly in Physics and natural sciences is expressed from the point of view of financial economics. The emphasis is given on its applicability in terms of finance and economic theory. Fourth part includes presentation and discussion of the empirical findings. The results are compared to those of Soytas and Sari (2006) to see the methodological effects, as well. The paper ends with suggestions for future research focusing on the financial or macroeconomic factors in chaotic and complex financial markets.

2. Literature Review

The causality relationship between energy consumption, growth, employment level or income is a well-studied research topic in financial economics. Ghali and El-Sakka (2004) argue a neoclassical production function with labour, capital stock and energy consumption. The function states that output, capital, labour, and electricity consumption move together in the long-run. Therefore, as Soytas and Sari (2006) stress, there might exist a long-run equilibrium relationship between the variables indicating Granger causality. By accepting both the arguments of Ghali and El-Sakka (2004) and Soytas and Sari (2006), we state that long-term memory of the financial variables in the chaotic economies might be captured by the wavelets methods which filter and clean the data from the short-term volatilities and chaotic patterns and display the long-term relationships among the variables.

The past researches use different econometric methodologies in testing the relationship among growth, income and energy consumption. Vector correction based causality test are used to detect the relationship. Cheng (1999), Eden and Jang (2002), Asafu (2000) find remarkable causalities among the mentioned variables in different economies by using cointegration tests detecting the long-term effects. The research of Masih and Masih (1996) should be emphasized in terms of both methodological and empirical reasons. They use a cointegration analysis and vector autoregressive model to examine the causal relationships among energy consumption, employment, and output for Taiwan over the period from January 1982 to November 1997. They find out that Granger causality tests based on vector error-correction models suggest bi-directional Grange causality for employment-output and employment-energy consumption, but only unidirectional causality running from energy consumption to output.

The research on the causality between the growth and energy consumption is in general in effort to find a distinguished difference between developed and developing countries. In theory, the degree of causality is waited to be stronger in developed economies. Reducing electricity consumption might have greater impact on growth in developed markets due to higher industrialization in those economies. The researches conducted by Dunkerly (1982), Jumbe (2004), Yong and Lee (1998), with data from emerging markets and those of Samouilidis and Mitropoulos (1992), Erol and Yu (1987) with data from advanced economies are also underlined in terms of their distinctive evidence on the issue between the types of economies.

Research on the electricity consumption and growth using data from Turkish economy is restricted. Soytas and Sari (2003) test the time series properties of energy consumption and GDP and reexamine the causality relationship between the two series in the top 10 emerging markets – excluding China due to lack of data – and G-7 countries. They find out bi-directional causality in Argentina, causality running from GDP to energy consumption in Italy and Korea, and from energy consumption to GDP in Turkey, France, Germany and Japan. Hence, energy conservation may harm economic growth in the last four countries. Sari and Soytas (2004) find that over a 3-year horizon the total energy consumption explains 21% of forecast error variance of GDP and it appears to be almost as important as employment in Turkey. Therefore, policy-makers may be interested in identifying the energy dependencies of economic growth in allocating the energy investment budget.

According to Ogulata (2002) the industrial sector energy consumption accounts for the highest share in the primary energy demand in Turkey. He also points out that electricity consumption is a major component in the primary energy demand of the Turkish industrial sector. To see the importance of gas energy for Turkey, the discussion article written by Kilic (2005) can be examined. According to Kilic (2005) energy demand of Turkey is growing by 8% annually, one of the highest rates in the world. In addition, natural gas consumption is the fastest growing primary energy source in Turkey. Gas sales started at 0.5 bcm (billion cubic meters), in 1987 and reached approximately 22 bcm in 2003. Turkey is an important candidate to be the "energy corridor" in the transmission of the abundant oil and natural gas resources of the Middle East and Middle Asia countries to the Western market. Ileri and Gurer (1998) also emphasize the increasing electricity demand in Turkey.

The paper employs wavelets in detecting long-term relationships among the variables. Wavelet transform is a multi-scale analysis method to detect the signal in different scales. In that way, insignificant high-frequency changes of the signal are filtered out and the empirical findings concentrate on long-term behaviours. Recent empirical findings in finance show that wavelets are good at capturing long-memory in time series. By employing wavelets to show the time-scale decomposition, Ramsey and Lampart (1998) examine the relationships among consumption, GDP, income and money. They conclude that the relationships bet ween the economic variables change in different scales. The other works that applied wavelet analyses for causal relationship are Kim and In (2003), Almasri and Shukur (2003), Zhang and Farley (2004) and Dalkır (2004).

To the extent of our knowledge, this paper is the first to examine the relationship between energy input and production by using wavelets. By wavelet correlation analysis and multi-scale causality test, the paper aims at scaling the causality and finds the long-term dependence in the time series. In the next part data and methodology used in this paper are introduced in detail.

3. Methodology and Data

3.1. Methodology

Wavelets theory is based on Fourier analysis which can be represented with the sum of sine and cosine functions. Fourier analysis or Fourier series can be represented as Equation (1).

$$f(x) = b_0 + \sum_{k=1}^{\infty} (b_k \cos 2\pi kx + a_k \sin 2\pi kx), \tag{1}$$

$$b_0 = \frac{1}{2\pi} \int_0^{2\pi} f(x)\,dx,$$

$$b_k = \frac{1}{\pi} \int_0^{2\pi} f(x)\,Cos(kx)\,dx,$$

$$a_k = \frac{1}{\pi} \int_0^{2\pi} f(x)\,Sin(kx)\,dx,$$

$a_{0,}$ a_k *ve* b_k can be solved with OLS. Fourier to wavelet transition is given as Equation (2).

$$f(x) = c_0 + \sum_{j=0}^{\infty} \sum_{k=0}^{2^j-1} c_{jk}\psi(2^j \chi - k), \tag{2}$$

$\psi(x)$ called as mother wavelet which is mother to all dilations and translations of ψ in Equation (2). A simple example of mother wavelet is (Tkacz, 2001) in Equation (3).

$$\Psi(x) = \begin{cases} 1 & : 0 \le x < \frac{1}{2} \\ -1 & : \frac{1}{2} \le x < 1 \\ 0 & : other \end{cases} \tag{3}$$

In high frequency finance the maximal overlap discrete wavelet transform (MODWT) is used instead of DWT as MODWT can handle any sample size *N* and wavelet variance estimator of MODWT is asymptotically more efficient than the estimator based on the DWT.

The MODWT is formulated with matrices (Gencay et al., 2002; Percival and Walden, 2000) and yields J vectors of wavelet filter coefficients $\tilde{W}$ j,t , for j=1,…,J and t=1,….,N/2j, and one vector of wavelet filter coefficients $\tilde{V}$ j, t through (Gallegati, 2005) Equations (4) and (5)

$$\widetilde{W}_{j,t} = \sum_{t=L_j}^{N} \tilde{w}_{j,t}^{X} f(t-1), \tag{4}$$

$$\widetilde{V}_{j,t} = \sum_{t=L_j}^{N} \tilde{v}_{j,t}^{Y} f(t-1), \tag{5}$$

where $w_{j,t}^{X}$ and $v_{j,t}^{Y}$ are the scaled wavelet and scaling filter coefficients.

Wavelet covariance between two series X_t and Y_t is defined as in Equation (6) (In and Kim, 2006).

$$Cov(\lambda_j) = \frac{1}{\tilde{N}} \sum_{t=L_j}^{N} \widetilde{W}_{j,t}^{X} \widetilde{V}_{j,t}^{Y}, \tag{6}$$

where, λ_j represents scale. MODWT estimator of the wavelet correlation can be expressed as in Equation (7) (In and Kim, 2006).

$$\tilde{\rho}(\lambda_j) = \frac{Cov(\lambda_j)}{\tilde{v}_X(\lambda_j)\tilde{v}_Y(\lambda_j)}, \tag{7}$$

where $\tilde{v}_X(\lambda_j)$ and $\tilde{v}_Y(\lambda_j)$ are wavelet variances estimated by the MODWT coefficients for scale λ_j described in Equations (8) and (9):

$$\tilde{v}_X(\lambda_j) = \frac{1}{\tilde{N}} \sum_{t=L_j}^{N} \left[\widetilde{W}_{j,t}^{X}\right]^2, \tag{8}$$

$$\tilde{v}(\lambda_j)_Y = \frac{1}{\tilde{N}} \sum_{t=L_j}^{N} \left[\widetilde{V}_{j,t}^{Y}\right]^2. \tag{9}$$

In order to apply wavelet analysis first unit root should be tested in time series. All series should be stationary at the same level. ADF test (Dickey ve Fuller, 1981) is widely used and can be determined as (10).

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t . \tag{10}$$

To test cointegration, we employ Johansen cointegration test offered by Johansen (1988) and Johansen and Joselius (1990).

We apply unrestricted cointegration test without trend and with constant term (11).

$$H_1^*(r): \prod y_{t-1} + Bx_t = \alpha(\beta' y_{t-1}) + \rho_0 . \tag{11}$$

Cointegration in stationary time series by Johansen procedure is set with trace and maximum eigenvalue statistics (12, 13)

$$\lambda_{trace(r)} = -T \sum_{i=r+1}^{k} In(1-\bar{\lambda}_i), r = 0,1,2,3,...., n-1 \tag{12}$$

$$\lambda_{\max(r,r+1)} = -TIn(1-\bar{\lambda}_{r+1}) . \tag{13}$$

If cointegration exists between variables it states that at least one directional causality exists (Granger, 1969). If cointegration doesn't exist between variables standart cointegration test (vector autoregression) is applied (Granger, 1969) and if cointegration exists between variables vector error correction model (Engle and Granger, 1987) should be applied (Granger, 1988). VECM based causality test is applied with Equations (14) and (15):

$$\Delta GDP_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta GDP_{t-i} + \sum_{i=1}^{n} \alpha_{2i} \Delta Energy_{t-i} + \sum_{i=1}^{n} \alpha_3 EC_{t-n} + \varepsilon_i , \tag{14}$$

$$\Delta Energy_t = \alpha_0 + \sum_{j=1}^{n} \alpha_{1j} \Delta Energy_{t-j} + \sum_{j=1}^{n} \alpha_{2j} \Delta GDP_{t-j} + \sum_{j=1}^{n} \alpha_3 EC_{t-n} + \varepsilon_j , \tag{15}$$

where EC_{t-n} parameter is error correction term and α_{1i}, α_{2i}, α_{1j} and α_{2j} parameters are short-run parameters. If there is long-run relationship as the variables are cointegrated, vector error correction model will be employed. From Equations (10) and (11), the null hypothesis that GPD/EC does not Granger cause EC/GDP in the short-run would be rejected if the lagged coefficients of α_{1S} were jointly significant based on a Standard Wald test (Shammugan *et al*., 2003). Optimal lag length of the cointegration and error correction model is determined by Schwartz Information Criteria.

There might be clustering of volatility in the residuals as the dependence is weak on the parameter (α). Since the data are not adequate to determine clustering of volatility, besides our main aim is to determine direct effect rather than volatility effect.

3.2. Data

This paper examines the causality between electricity use and output in the Turkish manufacturing sector in a multivariate setting. In that perspective, the research uses the theoretical relationship among changes in energy consumption and growth.

Electricity consumption is the input indicator and value added is the measure of output. The value added may be seen as the representation of the contribution of the manufacturing industry to the Turkish GNP. Electricity consumption might be seen as a proxy for energy consumption in the manufacturing sector. This research uses the same data within the same period employed by the Soytas and Sari (2006) research. Since the difference is in the methodology used, the sample period is fixed. However, fixed investment and labor in manufacturing industry used as one of the input variable in the research of Soytas and Sari (2006) are excluded from our research. Since the capital stock data are not readily available and difficult if not impossible to obtain, they assume a constant depreciation rate; and use variance in growth rate of fixed investment as the reliable proxy for variance in the growth rate of capital stock. We are not agree on the proxy role of the variable because of the assumption of constant depreciation rate. The paper uses, as parallel to the research of Soytas and Sari (2006), annual data for the period of 1968-2002. The data are sourced from Soytas and Sari (2006)[1] and log-returns of the variables are calculated. The explanations of the variables used in the analyses are as follows:

LEC = natural log of total electricity consumption in industry in 106 kW h.

LVA = natural log of value added-GNP manufacturing in billion TL (1998 prices).

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[1] We present our thanks to Soytas and Sari for their help in proving data and their recent research paper's draft (Soytas and Sari, 2006).

4. Empirical Results

In order to apply wavelet analysis first unit root and unit root level should be tested in time series. All series should be stationary at the same level. Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1981) is widely used and can be determined as in Equation (16)

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t \ . \qquad (16)$$

Table 1 shows ADF tests of level and log-differenced series. Lag lengths are determined with Schwartz Information Criteria in ADF test. Level series are not stationary where log-differenced series are stationary at the 1% significance level. So original and multi-scale series are tested as log-differenced level.

Table 1

Unit root test statistics of the time series

Variables	ADF Test	
	nl [a]	t-statistics
VA	2	-0.519534{<0.9}
EC	2	-0.327322{<0.95}
DLVA	0	-5.91364{<0.01}*
DLEC	0	-5.01811{<0.01}*

Notes. Lag length is determined as max. 12 in accordance with Schwartz Information Criteria. The values on paranthesis are the reject statistics for the unit roots. [a] Lag length. Tests for prices in level use a constant but not a time trend. The table reports results of the augmented Dickey-Fuller (Dickey and Fuller, 1981) tests for all the time series. The number of lags (nl) in the tests have been selected using the Schwarz information criterion with a maximum of twelve lags. Probability of the statistic exceeding the computed value under H_0 is given in braces.

* indicates the rejection of the unit root null at the 1% significance level.

We test if all the scaled series are stationary with ADF Test. The results of the unit root test in Table 2 show that all of the time-scaled variables are stationary on level. In that respect, cointegration test and wavelet analysis can be employed.

Table 2

Unit root test statistics of the scaled time series

	ADF Test	
Variables	nl	t-stat.
DLVA_DJT1	1	-11.2536 {<0.01}*
DLEC_DJT1	3	-6.85783 {<0.01}*
DLVA_DJT2	3	-5.99742 {<0.01}*
DLVA_DJT2	3	-6.53789 {<0.01}*
DLEC_DJT3	1	-5.36138 {<0.01}*
DLVA_DJT3	1	-4.2144 {<0.01}*
DLEC_DJT4	1	-5.24854 {<0.01}*
DLEC_DJT4	1	-4.93221 {<0.01}*
DLVA_DJT5	2	-2.79693 {<0.05}
DLEC_DJT5	1	-6.14593 {<0.01}*

Notes. The table reports results of the augmented Dickey-Fuller tests for all the time series. The number of lags (nl) in the tests has been selected using the Schwarz information criterion with a maximum of twelve lags.

Probability of the statistic exceeding the computed value under H_0 is given in braces.

* indicates the rejection of the unit root null at the 1% significance level.

Johansen cointegration test (Johansen, 1988, and Johansen and Joselius, 1990) results in Table 3 show that original data (GNP and electricity consumption represented as LDVA and LDEC) are cointegrated with three lags where time-scaled data are cointegrated with one lag. This result shows that at least one directional causality exists between GNP and electricity consumption and time-scaled production and electricity consumption at all time-scaled level for Turkish economy.

Table 3

Cointegration test results

		Unrestricted Cointegration Rank Test		
DLVA & DLEC	nl		**Trace Stat.**	**Max-Eigen Stat.**
DLVA & DLEC	3	r=0 r≤1	23.4604{<0.02}* 7.27366 {<0.2}	16.1867 {<0.05}* 7.27366 {<0.2}
DJT1 (2 years)	1	r=0 r≤1	91.9121 {<0.01} 32.0666 {<0.01}	59.8455 {<0.01} 32.0666 {<0.01}
DJT2 (3-4 years)	1	r=0 r≤1	107.556 {<0.01} 35.9598 {<0.01}	71.5965 {<0.01} 35.9598 {<0.01}
DJT3 (5-8 years)	1	r=0 r≤1	44.0876 {<0.01} 16.6289 {<0.01}	27.4587 {<0.01} 16.6289 {<0.01}
DJT4 (9-16 years)	1	r=0 r≤1	21.2946 {<0.01} 3.58448 {<0.5}	24.8791 {<0.01} 3.58448 {<0.5}
DJT5 (17-32 years)	1	r=0 r≤1	80.9206 {<0.01} 45.7239 {<0.01}	126.645 {<0.01} 45.7239 {<0.01}

* indicates significance of cointegration. nl represents lag length that is selected with Schwarz Selection Criteria. Probability of the statistic exceeding the computed value under H_0 is given in braces.

Vector error based causality test results for original and time-scaled variables are shown in Table 4. These results indicate that VA and EC caused each other in the short run as wald test χ^2 value and error correction parameters of the original data are statistically significant. Wald test χ^2 values and error correction parameters, EC_{t-1}, are statistically significant until 3rd time-scale for EC → VA model and thus indicate that Error EC affected VA until 3-4 years. Error correction parameters, EC_{t-1}, are statistically significant for 1st, 2nd and 4th time-scales for VA → EC and thus indicate that VA affects EC in the short run and in the long run as 1-2 and 5-8 years. Thus how is that in the short run there is feedback relationship between GNP and energy consumption, while in the long run (for 5-8 years) GNP leads to energy consumption.

Table 4

Vector error correction based causality/multi-scale causality test

LDVA	nl [a]	Wald test	EC_{t-1}	Long-run Causality
LDEC → LDVA	1	14.3652 [0.0002] **	0.747262 [0.001]	EC => VA
DJT1 (2 years)	**1**	**22.7675 [0.0000] ****	**0.759310 [0.000]**	EC => VA
DJT2(3-4 years)	**1**	**5.59757 [0.0180] ***	**0.727128 [0.024]**	EC => VA
DJT3 (5-8 years)	**1**	**0.0144491 [0.9043]**	**0.126529 [0.905]**	**EC ≠> VA**

Table 4 (continued)

LDVA	nl [a]	Wald test	EC_{t-1}	Long-run Causality
DJT4 (9-16 years)	**1**	**0.795032 [0.3726]**	**0.237524 [0.379]**	**EC ≠> VA**
DJT5 (17-32 years)	**1**	**0.00246801 [0.9604]**	**-4.58328 [0.961]**	**EC ≠> VA**
LDEC	**nl [a]**	**Wald test**	**EC_{t-1}**	**Long-run Causality**
LDVA → LDEC	1	11.0907 [0.0009] **	0.644120 [0.002]	VA => EC
DJT1 (2 years)	**1**	**19.2066 [0.0000] ****	**0.634292 [0.000]**	VA => EC
DJT2 (3-4 years)	1	2.67607 [0.1019]	0.392138 [0.112]	VA ≠> EC
DJT3 (5-8 years)	1	11.1192 [0.0009] **	1.07144 [0.002]	VA => EC
DJT4 (9-16 years)	1	6.00227 [0.0143] *	0.45167 0.2012	VA ≠> EC
DJT5 (17-32 years)	1	22.4727 [0.0000] **	0.42578 [0.879]	VA ≠> EC

* %1, ** %5 represent acceptance of causality respectively. [] represent t-values. [a] Lag lengths. nl represents lag length that is selected with Schwarz Selection Criteria.

MODWT wavelet coefficients of VA and EC and Scatter plot of time-scaled VA and EC are shown in Figure 1 and Figure 2. The graphs show that VAs and ECs coefficients move together at 3rd time-scale (DJT3-5-8 years). As shown in Figure 3 Wavelet correlation between VA and EC is also maximum at 3rd time-scale as %90,08. Since the magnitude of the wavelet correlation changes based on time-scales indicating that VA and EC are fundamentally different[1] (In and Kim, 2006).

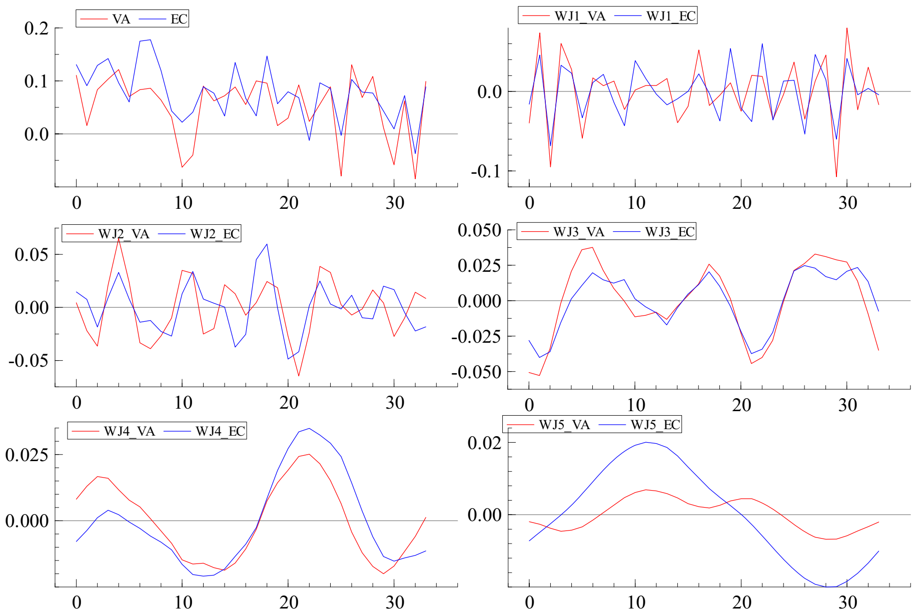
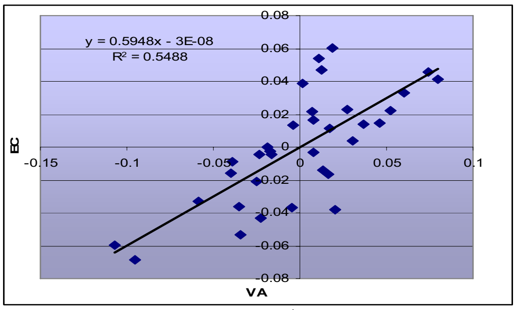
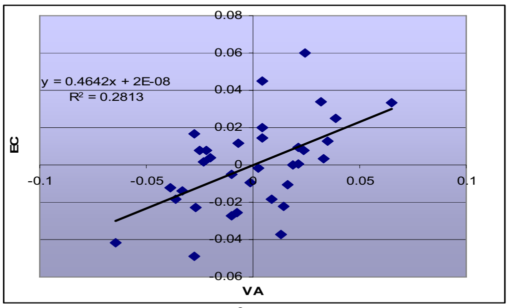


Fig. 1. MODWT wavelet coefficients of VA and EC

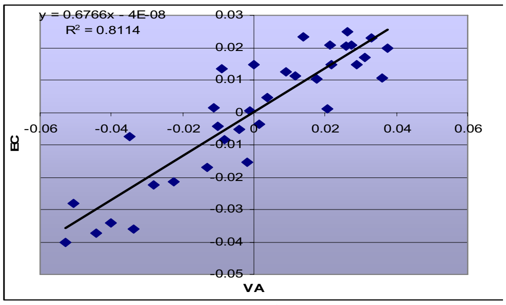
[1] In and Kim (2006) also estimated wavelet correlation for the stock and the futures markets and found that both are not fundamentally different as magnitude of the correlation increases as the time scale increases.



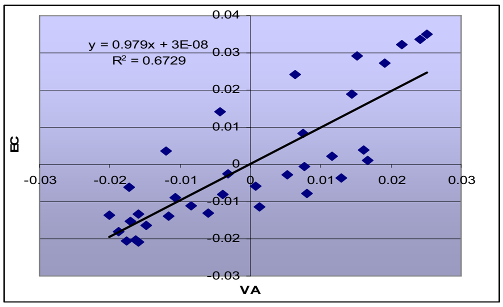
DJT01 (2^1 years)



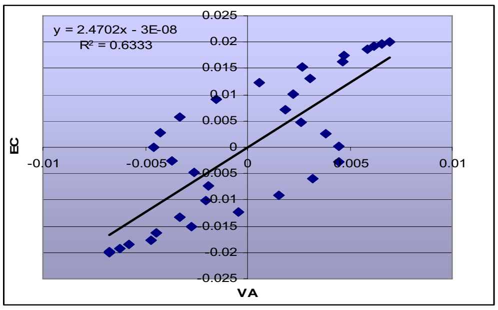
DJT02 (2^2 years)



DJT03 (2^3 years)



DJT04 (2^4 years)



DJT05 (2^5 years)

* DJT01 2 years, DJT02 3-4 years, DJT03 5-8 years, DJT04 9-16 years, DJT05 17-32 years

Fig. 2. Scatter plot of time-scaled VA and EC*

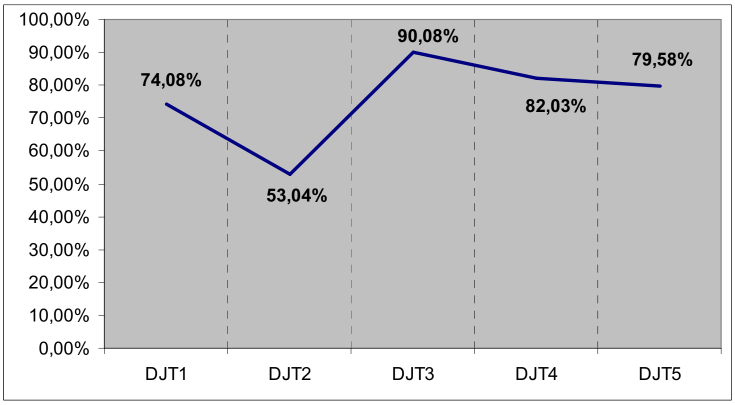


Fig. 3. Estimated wavelet correlations between VA and EC

5. Concluding Remarks

Tests results for causality between energy consumption and economic growth do not have a consensus in the financial economics literature. Empirical evidence varies on the economies examined and methodology employed. This paper proposes a wavelet analysis as a semi-parametric model for detecting multi-scale causality between electricity consumption and growth in emerging economies. To the best of our knowledge this paper is the first one that examines GNP and energy consumption integration with wavelet analysis.

Using wavelet analysis we find that in the short run there is feedback relationship between GNP and energy consumption, while in the long run GNP leads to energy consumption. Wavelet correlation between GNP and energy consumption is maximum at 3^{rd} time-scale (5-8 years) and this shows that GNP affects electricity consumption maximally around 5-8 years later in the long-run. We also find that the magnitude of the wavelet correlation changes based on time-scales for GNP and energy consumption and thus indicates that VA and EC are fundamentally different in the long run.

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