**An Investigation of the Energy Consumption-Growth Nexus in the Arab Countries**

Leila Dagher

Assistant Professor of Economics

American University of Beirut

Email: [ld08@aub.edu.lb](mailto:ld08@aub.edu.lb)

**ABSTRACT**

A thorough examination of the relationship that exists between energy consumption and economic growth in the Arab countries is essential for at least two reasons. First, existing studies on individual countries or group of countries from our sample have provided conflicting results. Second, the type of relationship that exists between energy consumption and economic growth has policy implications of critical importance; for example if a unidirectional relationship running from energy consumption to economic growth is found, then the economy is an energy dependent one and any energy policy encouraging conservation might adversely affect economic growth. This topic is very timely since many Arab countries have recently developed or are currently developing national energy policies that involve an energy conservation target. Consequently, this paper conducts a full-fledged study in both a bivariate and a multivariate setting, using a battery of causality tests in an effort to obtain robust results of the energy-gdp nexus in 15 Arab countries. We will conclude our investigation with a list of suggestions and implications relevant to policy-making in the energy sector.

**INTRODUCTION**

Since the seminal study of Kraft and Kraft (1978), probably motivated by the oil price shock of 1973, the relationship between energy consumption and economic growth, aka the energy-gdp nexus has been abundantly studied.Examining the energy-gdp nexus is of interest mainly due to its far-reaching policy implications. The type of relationship can be classified into four testable hypotheses. First, if a unidirectional relationship running from energy consumption to economic growth is found, then the economy is said to be an energy dependent one and any energy policy encouraging conservation might adversely affect economic growth. This is known as the growth hypothesis. Second, if the inverse relationship is found, i.e. causality running from gdp to energy consumption, then energy policy will not affect growth, but changes in GDP will directly result in changes in energy consumption. This is known as the conservation hypothesis. Third, a bidirectional or mutual relationship confirms what is known as the feedback hypothesis. In the fourth case, no evidence of any relationship between the two variables is found. This is often referred to as the ‘neutrality hypothesis.’ In the first three cases, national energy and environmental policies must be carefully designed to take the energy-gdp relationship into consideration.

As a result of the growing interest in climate change and the focus of mitigation activities on the energy sector, as well as the rising cost of energy, energy conservation policies have seen a strong come-back in many countries. However, as can be seen from the relationships presented above, at least in one of the cases, such a policy might negatively impact the economy.

In this paper, we examine the case of the Arab countries. At least two factors render our attempt particularly valuable. First, existing studies on individual countries or group of countries from our sample have provided conflicting results, probably due to the use of different models, causality tests, sample periods, etc. Our study aims to find a robust set of results by using different model specifications, a multitude of causality tests, and investigating the sensitivity of the results to varying factors such as those mentioned above.

Second, the type of relationship that exists between energy consumption and economic growth has policy implications of critical importance, especially since many Arab countries have recently developed or are currently developing national energy policies that involve an energy conservation target. If, for example, evidence is found that causality runs from energy to GDP then an energy conservation target might have a negative impact on GDP growth. This study aims at providing insights regarding the role of energy consumption in economic development that can serve as a basis for future energy policies. Hence, our findings are expected to be of interest to both analysts and policy-makers, helping the latter group in shaping any future policy in that respect.

Our dataset, kindly provided to us free of charge by OAPEC (Organization of Arab Petroleum Exporting Countries), spans the period 1980-2009. We hope that with the interesting mix of countries we are examining, to be able to determine if the energy-gdp relationship is a function of whether a country is a net oil exporter or a net oil importer. Furthermore, by using both a time-series and a panel data approach, we hope to find out if there any notable differences between the results obtained from the individual treatment of countries versus the collective treatment, and if these differences can help explain some of the conflicting results found in the existing literature.

**LITERATURE REVIEW**

Some researchers have chosen to examine single countries, while others have studied several countries simultaneously in a panel data analysis framework. Typically, aggregate energy consumption is used as a proxy for energy consumption, but sometimes more disaggregated levels (e.g. residential, commercial, etc.) or specific energy sources have been examined (coal, nuclear, etc.). The main trend tends to be a bivariate analysis; the two variables being energy consumption and gdp (see, *inter alia*, Altinay and Karagol, 2004; Ghosh, 2002; Soytas and Sari, 2003; Yoo, 2005). Bivariate models are especially attractive in that they can be used for countries that suffer from a complete lack of data on some variables of interest (Zachariadis, 2007), as is typical in many developing countries. In a recent survey, Payne (2010) notes that 26 of the 35 studies surveyed employ bivariate models. Some other studies have conducted multivariate analyses based on theoretical considerations such as demand or production functions. The former typically include the price of energy as a third variable (see, *inter alia*, Asafu-Adjaye, 2000; Bloch et al., 2011; Masih and Masih, 1997, 1998) and the latter usually include measures for capital and labor ( see, *inter alia*, Apergis and Payne, 2009a, 2009b; Oh and Lee, 2004; Stern, 1993, 2000; Wolde-Rufael, 2009).

Recently, some studies have tried to find linkages with the environmental pollution-economic growth nexus usually investigated within the “Kuznets Curve” framework, and have thus included emissions as a third variable in their model (see, *inter alia*, Menyah and Wolde-Rufael, 2010; Nasir and Rehman, 2011; Pao and Tsai, 2010).

Generally speaking, existing studies have yielded conflicting results even for the same country. Researchers have attributed this divergence to differences in model specifications, sample periods, and estimation and testing methodologies (Apergis and Payne, 2011). An exhaustive review of the literature can be found in Payne (2010) or Ozturk (2010). Overall, these reviews highlight the importance of using large samples and multivariate models, when data availability allows that.

Besides the immediate policy implications of the energy-gdp nexus, some researchers have gone one step further in their policy recommendations, by concluding which countries can successfully implement the Kyoto Protocol without hurting their economic growth and which ones cannot (Lee, 2006). Also, some researchers suggest that energy resource endowment might have an impact on the direction of causality. For example, Wolde-Rufael (2009) finds evidence supporting the growth hypothesis in oil rich countries, while Al-Iriani (2006), in contrast, finds support for the conservation hypothesis for the Gulf Cooperation Council (GCC) countries. Examining a group of African countries, Eggoh et al. (2011) find evidence that the energy consumption-economic growth relationship is different for energy exporters versus energy importers.

A few studies suggest that countries in comparable stages of development can adopt similar energy policies and strategies, because the causal relationship between energy consumption and growth depends in part on the country’s stage of development. Apergis and Payne (2011) categorize 88 countries into four panels based on the World Bank income classification and conduct a multivariate panel analysis. They conclude that the relationship between electricity consumption and growth is a function of a country’s stage of development. Bildirici and Kayikci (2012), in their turn, divide the Commonwealth of Independent States into three groups based on the income per GDP level and investigate the electricity-growth nexus by group. Similarly to Apergis and Payne (2011), they find that the electricity-gdp relationship does differ across groups.

In contrast, other studies have suggested that the energy-growth nexus is country specific, and hence one cannot generalize to include countries in the same stage of development or in the same geographical region. Akinlo (2008) explores the energy-growth relationship in 11 sub-Sahara African countries, and concludes that African countries cannot adopt the same energy conservation policies, but rather each country needs to develop its own energy strategy based on its peculiar characteristics. Similarly, Acaravci and Ozturk (2010) find different energy-growth relationships for each member of a set of 19 developed European countries. The results for 4 Asian developing countries investigated by Asafu-Adjaye (2000) and 8 newly industrialized Asian countries investigated by Chiou-Wei et al. (2008) also confirm the hypothesis that the energy-growth relationship is not determined by the level of development in a country.

**ECONOMETRIC METHODOLOGY**

This section discusses the econometric procedures undertaken to test the direction of causality between the two variables – energy consumption (hereafter *E*) and real GDP (hereafter *Y*) in 15 Arab countries. Despite the well-known advantages of using multivariate models, in this paper we base our analysis on a bivariate model due to the lack of data which is not uncommon in developing countries. Most of the researchers who caution against the use of bivariate models also stress the importance of using large sample sizes, which according to Zachariadis (2007) include more than 35 observations. Our dataset, kindly provided to us free of charge by OAPEC (Organization of Arab Petroleum Exporting Countries), span the period 1980-2009 resulting in 30 observations, which again is typical for developing countries.

***Unit root and cointegration testing***

Typically, the first step in any time-series study is to check the order of integration of the variables in question. The Augmented Dickey Fuller (ADF) test (Dickey and Fuller 1979, 1981) will be used, complemented with the Phillips Perron (PP) test (Philips and Perron, 1988). Both tests are based on equation 1 in which the null hypothesis is , i.e. y has a unit root, and the alternative hypothesis is , but the test statistics are calculated differently.

(1)

where is assumed to be a Gaussian white noise error, *t* is a time trend, and the number of lags *p* is selected by the Akaike information criterion, where the maximum number of lags is calculated by Schwert’s (1989) formula . The distribution of does not follow the conventional *t* distribution, and hence the appropriate critical values are taken from MacKinnon (1996).

If the unit root tests confirm that at least some of the variables are I(1), then the next step would be to test if they are cointegrated, i.e. if they are bound by a long-run relationship. Cointegration exists between a set of non-stationary variables when a certain linear relationship of the series is stationary (Wang, 2003). To test for cointegration Johansen’s (1988, 1991) approach will be used. If cointegration is found then the remaining analysis should be perfomed using a VECM, otherwise the I(1) variables are differenced and a simple unrestricted VAR can be used.

***VAR model***

The vector autoregression (VAR) model, originally advocated by Sims (1980) as an alternative to simultaneous equation models, carries many advantages. Its ease of estimation (OLS),[[1]](#footnote-1) ease of construction by treating all variables as endogenous, and good forecasts have made it one of the most widely used models in spite of some criticism surrounding the model (see for e.g. Cooley and Leroy, 1985; Harvey, 1997; Runkle, 1987). It is worth noting that its major drawback is the large number of parameters to be estimated (*N*+*pN2*), which may severely limit degrees of freedom. VARs have been used primarily in forecasting, testing Granger causality, and studying the effects of policy through impulse response characteristics (Greene, 2003). The VAR model in reduced form is given by:

(2)

where is a vector of N stationary variables, is a vector of Gaussian white noise errors, and *p* is the order of the VAR. If the variables being studied are I(1) but not cointegrated, they can be used in differenced form in a VAR. Otherwise, if the variables are I(1) and cointegrated, a vector error correction model can be employed.

It is essential to appropriately specify the lag length *p* for the VAR system; if *p* is too small the model is misspecified and the missing variables create an omitted variables bias, while overparameterizing involves a loss of degrees of freedom. VAR estimates are known to be sensitive to the number of lags included. The lag length *p* will be determined based on Akaike’s Information Criterion (1973) AIC, where the maximum number of lags is calculated by Schwert’s (1989) formula .

This method of analysis permits us to test for the direction of causality, if it exists, as discussed next. Moreover, it captures the dynamics of the interrelationships between the variables through impulse responses and variance decomposition.

***Granger Causality Testing***

One of the earliest methods to test for causality was proposed by Granger (1969). Granger (1988) defines causality as “if *yt* causes *xt*, then *xt+1* is better forecast if the information in *yt-j* is used than if it is not used.” To determine the direction of causality, a simple Wald test in an unrestricted VAR setting is applied to a group of coefficients to test whether they are jointly significant or not.

Consider the VAR model presented in equations 3 and 4, where *Y* denotes the logarithm of GDP and *E* denotes the logarithm of energy consumption. In order to identify the direction of the causality between *Y* and *E*, Granger Causality tests are applied to the VAR model as follows.

In Equation 3 if then *Y* does not Granger cause energy consumption, while if the opposite is true then *Y* can be said to Granger cause *E*. Similarly, in Equation 4 we test whether the group of coefficients are jointly significant or not to conclude whether *E* Granger causes *Y* or not. *P* is usually determined based on a lag selection criterion such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC).

(3)

(4)

where and are white noise error processes. This simple Wald test, however, is only valid if all variables are stationary (Granger, 1969; Granger and Newbold, 1974). Otherwise, the test will have nonstandard distributions (Sims et al., 1990; Toda and Phillips, 1993), and hence other tests must be used. In the context of studying the energy-gdp relationship, it has been frequently found that either one or both of the variables of interest contain a unit root. This explains the shift from using Granger’s test in earlier studies to using alternative tests (such as Hsiao, Toda-Yamamoto, or Granger causality on a vector error correction model (VECM)) since the 1980s. Another drawback of Granger’s test, is that the causality results are very sensitive to the selected lag length (Chontanawat et al., 2008).

In response to the criticisms regarding the lag length selection under Granger’s test, Hsiao (1981) proposed a modified version of the test that uses Akaike’s Final Prediction Error (FPE) criterion (Akaike, 1970) to select the lag length of each of the variables. The first step is to determine the number of lags *n* that minimizes the FPE of equation 1 without any *Y* lags. Once *n* is set, we start varying the number of lags of the second variable, *Y*, to find *m*, the number of lags that minimizes the FPE. The FPEs from both steps (with lags of *Y* and without) are then compared; if FPE(*n,0*) is smaller than FPE(*n,m*), then we can conclude that GDP does not cause energy consumption and vice versa. A similar procedure is applied to equation 2 to find out if energy consumption causes GDP or not by comparing FPE(*s,0*) to FPE(*s,r*). The Hsiao test can be applied regardless of the integration order or cointegration properties of the original variables involved, as long as the variables in their final transformed forms are stationary; some series might need differencing to attain stationarity (Hsiao, 1981).

Toda and Yamamoto (1995), TY hereafter, propose a causality test that involves a modified Wald test on an augmented VAR specification. In the TY causality test, the optimal lag length is selected based on one of the typical lag selection procedures and then the VAR () is augmented by the maximum order of integration of the variables, *m*, to obtain a VAR(*l+m*). Typically, in applications such as ours *m* ranges between 0 and 2. Consider the following VAR(*l*) specification:

(5)

(6)

We then augment each of the two equations with *m* lags

(7)

(8)

The VAR(*l+m*) is now estimated using a seemingly unrelated regression (SUR) procedure. Tests for the significance of coefficients are conducted by ignoring the last *m* lags added to the VAR. For instance, to study whether Granger causes in the system above, the joint significance of the *βs* should be examined for the first terms in equation 5. If the null hypothesis cannot be rejected then we conclude that does not Granger cause, and vice versa. Similar steps are followed to test whether there exists a causality relationship from *E* to *Y* or not, this time by examining equation 6. The test statistic is a Wald statistic having an asymptotic distribution with *l* degrees of freedom.

Unlike Granger’s test, the TY approach can be applied to both stationary and non-stationary variables. Moreover, in contrast to the Hsiao test, variables can still be used in levels even if they contain a unit root. By intentionally adding m lags to the VAR(*l*), the TY procedure avoids any biases related to unit root and cointegration testing and hence increases the robustness of the results. Clarke and Mirza (2006) compare different causality tests and conclude that the TY exhibits more consistent performance and seems to be superior to the pretesting approaches, which include Johansen (1988) and Engle and Granger (1987). Also, the size of the TY test has been found to be acceptable, however the test has been criticized for being inefficient since it overfits the VAR and consequently suffers from low power (Kuzozumi and Yamamoto, 2000).

To distinguish between the short-run and the long-run relationship between energy consumption and growth, the traditional methodology of testing for unit roots and cointegration must be followed. In case at least one cointegrating relationship was found, then based on the Granger Representation Theorem, Granger (1988) shows that if a pair of I(1) series are cointegrated, then a causal relationship exists in at least one direction. The dynamic Granger causality can be captured from the vector error correction model derived from the long-run cointegrating relationship (Granger, 1988). Assuming *E* and *Y* are found to be cointegrated, then in an effort to capture SR and LR sources of causality between the variables, the VECM of equations 7 and 8 can be estimated.

(7)

(8)

where ECT denotes the error correction term which represents the cointegrating or long-run relationship between the two variables. To test for LR causality in equation 7, we test the following null hypothesis , if we reject the null then *Y* granger-causes *E* in the long run and vice versa. A similar test can be applied on in equation 8 to check if *E* granger causes *Y* in the LR or not. Short run causality from *Y* to *E* is detected if the null hypothesis can be rejected, otherwise we conclude that *Y* does not granger cause *E* in the SR. Similarly, to check for SR causality from *E* to *Y* in equation 8, we test if or not.

***Impulse Response Function (IRF)***

The causality tests discussed above only show the type of causal relationship between two variables. In order to examine how long these impacts will remain effective, we use the impulse response and variance decomposition analyses (Bloch et al., 2011). Impulse response analysis is a useful tool to examine the effect of a shock over time on the various variables in a system. For example, if we introduce a one period shock to *E* by increasing by one standard deviation at time t=0 (see equation 3), we can observe how this impulse will affect *Y* immediately and several periods later. However, if the errors are correlated as is usually the case, we cannot associate a shock with any one particular variable. In that case and in order to be able to isolate the effects of any specific shock, researchers have used orthogonalized impulses based on the Cholesky decomposition.

Assuming that the VAR in equation 2 is stable, by repetitive substitution we obtain the following moving average representation of the VAR:

Where

And with

A shock to a stationary time series is known to be transitory. In other words, for an I(0) series the impact of a shock will disappear after some time period when the series will revert to its mean value.

To isolate the impact of one shock from the effect of other shocks in the system, orthogonalized impulse responses are applied. Orthogonalization can be achieved through Choleski factorization, which is not invariant to the ordering of the variables in the VAR. The first variable in the ordering is the one which is the least influenced by other variables in the model, similar to an exogenous variable. The variable that is influenced by other variables the most is chosen as the last variable in the ordering.

Using the Cholesky decomposition, the variance-covariance matrix of the errors can be uniquely decomposed into , where is a lower triangular matrix with ones on the diagonal and is a diagonal matrix (Kennedy, 2003). The errors can thus be transformed into orthogonal errors with a variance-covariance matrix D.

Or more compactly (9)

Where

Applying the Cholesky decomposition to the moving average representation of equations 3 and 4, we obtain

(10)

The four sets of coefficients are called the impulse response functions. For example, and are the one-period responses of an impulse in on and , respectively.

***Variance Decomposition (VD)***

Another way of characterizing the dynamics of a VAR is via the variance decomposition. Forecast error variance decomposition is applied to identify the relative importance of a variable in generating its own variation. Similarly to the IRF, the results are sensitive to the ordering of the variables.

In general, the n-step ahead conditional forecast of using equation 3 is:

And hence the n-period forecast error will be

For example if we focus solely on the sequence in (4), the n-step ahead forecast error is:

And its variance denoted by is:

We are now ready to decompose the n-step ahead forecast error variance into the proportions due to each of the and shocks, shown below respectively:

The sum of the variance decompositions of any variable as shown above should equal 100 per cent. Note that if the variance decomposition due to an impulse in for example is zero for all *n*, then we can say that is exogenous. Enders (2010) recommends examining the variance decompositions at various forecast horizons. Consequently, we will look at the 1 year and 2 year variance decompositions.

***Panel Data Analysis***

In addition to the TS analysis on each individual country, we plan to conduct a panel analysis, which benefits from more degrees of freedom and higher efficiency compared to TS models. Panel unit root tests are based on Im et al. (2003), which has an advantage over the Breitung (2000) and the Levin et al. (2002) tests of being less restrictive; the coefficient on the lagged variable is allowed to vary across the cross-sectional units. Panel cointegration tests will be performed following the Pedroni (1999, 2000, 2001, 2004) approach, which reports statistics for 7 tests (4 are panel tests and 3 are group tests). If evidence of cointegration is found, a panel VECM is estimated using the fully modified ordinary least square estimator (Pedroni, 2000), on which SR and LR causality tests can be applied similarly to the case above.

**REFERENCES**

Acaravci, A., Ozturk, I., 2010. On the relationship between energy consumption, CO2 emissions, and economic growth in Europe. Energy, doi:10.1016/j.energy.2010.07.009.

Akaike, H., 1970. Statistical predictor identification. Annals of the Institute of Statistical Mathematics, 22, 203– 217.

Akaike, H. (1973), "Information Theory and an Extension of the Maximum Likelihood Principle", *Second International Symposium on Information Theory* (B.N. Petrov and F. Csaki, eds.), 267-281. Budapest : Academia Kiado.

Akinlo, A. E., 2008. Energy consumption and economic growth: Evidence from 11 Sub-Sahara African countries. Energy Economics, 30, 2391-2400.

Al-Iriani, M.A., 2006. Energy-GDP relationship revisited: an example from GCC countries using panel causality. Energy Policy, 34 (17), 3342- 3350.

Altinay, G., Karagol, E., 2004. Structural break, unit root, and the causality between energy consumption and GDP in Turkey. Energy Economics, 26(6), 985–994.

Apergis, N., Payne, J.E., 2009a. Energy consumption and economic growth in Central America: evidence from a panel cointegration and error correction model. Energy Economics, 31, 211–216.

Apergis, N., Payne, J.E., 2009b. Energy consumption and economic growth: Evidence from the Commonwealth of Independent States. Energy Economics, 31, 641-647.

Apergis, N., Payne, J. E., 2011. A dynamic panel study of economic development and the electricity consumption-growth nexus. Energy Economics, 33 (5), 770- 781.

Asafu-Adjaye, J., 2000. The relationship between energy consumption, energy prices and economic growth: time series evidence from Asian developing countries. Energy Economics, 22, 615– 625.

Bildirici, M. E., Kayikci, F., 2012. Economic growth and electricity consumption in former Soviet Republics. Energy Economics, doi:10.1016/j.eneco.2012.02.010.

Bloch, H., Shuddhasattwa, R., Salim, R., 2011. Coal consumption, CO2 emission and economic growth in China: empirical evidence and policy responses. Energy Economics, doi:10.1016/j.eneco.2011.07.014.

Breitung, J., 2000. The local power of some unit root tests for panel data. In: Baltagi, B.H. (Ed.), Nonstationary Panels, Panel Cointegration and Dynamic Panels. Elsevier, Amsterdam, pp. 161–177.

Chiou-Wei, S. Z., Chen, C., Zhu, Z., 2008. Economic growth and energy consumption revisited – Evidence from linear and nonlinear Granger causality. Energy Economics, 30, 3063-3076.

Chontanawat J., Hunt L., Pierse R., 2008. Does energy consumption cause economic growth?:Evidence from a systematic study of over 100 countries. Journal of Policy Modeling, 30, 209-220.

Clarke, J., Mirza, S.A., 2006. Comparison of some common methods of detecting Granger noncausality. Journal of Statistical Computation and Simulation, 76, 207–231.

Cooley, Thomas F., and Stephen F. Leroy. “Atheoretical Macroeconometrics: A Critique,” Journal of Monetary Economics, vol. 16 (June 1985), pp. 283–308.

Dickey, D.A. and W.A. Fuller (1979), “Distribution of the Estimators for Autoregressive Time Series with a Unit Root,” *Journal of the American Statistical Association*, 74, p. 427–431.

D.A. Dickey and W.A. Fuller (1981), Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, **49**, 1057-1071.

Dolado, J., Jenkinson, T., Sosvilla-Rivero, S., 1990. Cointegration and unit roots. Journal of Economic Surveys, 4, 249-273.

Eggoh, J. C., Bangake, C., Rault, C., 2011. Energy consumption and economic growth revisited in African countries. Energy Policy, 39, 7408-7421.

Enders, W. 2010. Applied econometric time series. Wiley.

Engle, R.F., Granger, C.W.J., 1987. Cointegration and error correction: representation, estimation and testing. Econometrica, 55, 251– 276.

Ghosh, S., 2002. Electricity consumption and economic growth in India. Energy Policy 30, 125–129.

Granger, C.W.J., 1969. Investigating causal relation by econometric and cross- sectional method. Econometrica 37, 424–438.

Granger, C.W.J., 1988. Some recent developments in a concept of causality. Journal of Econometrics, 39, 199– 212.

Granger, C.W.J., Newbold, P., 1974. Spurious regressions in econometrics. Journal of Econometrics, 2, 111–20.

Greene, W. 2003. Econometric Analysis. 5th edition. Pearson Education: New Jersey.

Harvey, A.C. (1981). The Econometric Analysis of Time Series. Philip Alan, Oxford.

Hsiao, C., 1981. Autoregressive modeling and money income causality detection. Journal of Monetary Economics 7, 85– 106.

Huang, B.N., Hwang, M.J., Yang, C.W., 2008. Causal relationship between energy consumption and GDP growth revisited: a dynamic panel data approach. Ecological Economics 67, 41–54.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. Journal of Econometrics 115, 53–74.

Johansen, S. 1988. Statistical analysis of cointegration vectors. Jouornal of Economic Dynamics and Control 12, 231-254.

\_\_\_\_\_\_\_\_\_\_\_ 1991. Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models. Econometrics, 59, 1551-1580.

Kennedy, P. 2003. A Guide to Econometrics. 5th Edition. Cambridge: MIT press.

Kraft, J., Kraft, A., 1978. On the relationship between energy and GNP. Journal of Energy and Development 3, 401– 403.

Kuzozumi, E., Yamamoto, T., 2000. Modified lag-augmented autoregressions. Econometric Review, 19, 207– 231.

Lee, C.C., 2006. The causality relationship between energy consumption and GDP in G-11 countries revisited. Energy Policy, 34, 1086– 1093.

Levin, A., Lin, C.-F., Chu, C.S.J., 2002. Unit root tests in panel data: asymptotic and finite sample properties. Journal of Econometrics 108, 1–24.

MacKinnon, J. 1996. "Numerical Distribution Functions for Unit Root and Cointegration Tests", *Journal of Applied Econometrics*, Vol. 11, No. 6, pp. 601-618.

Masih, A.M.M., Masih, R., 1997. On the temporal causal relationship between energy consumption, real income, and prices: some new evidence from Asian-energy dependent NICs based on a multivariate cointegration/vector error correction approach. Journal of Policy Modeling, 19 (4), 417– 440.

Masih, A.M.M., Masih, R., 1998. A multivariate cointegrated modelling approach in testing temporal causality between energy consumption, real income and prices with an application to two Asian LDCs. Applied Economics, 30 (10), 1287– 1298.

Menyah, K., Wolde-Rufael, Y., 2010. Energy consumption, pollutant emissions and economic growth in South Africa. Energy Economics, 32, 1374- 1382.

Narayan, P.K., Smyth, R., 2005. Electricity consumption, employment and real income in Australia: evidence from multivariate Granger causality tests. Energy Policy 33, 1109– 1116.

Nasir, M. Rehman, F. U., 2011. Environmental Kuznets Curve for carbon emissions in Pakistan: An empirical investigation. Energy Policy, 39, 1857-1864.

Oh, W., Lee, K., 2004. Causal relationship between energy consumption and GDP revisited: the case of Korea 1970–1999. Energy Economics 26 (1), 1– 177.

Ozturk, I., 2010. A literature survey on energy-growth nexus. Energy Policy 38 (1), 340–349.

Pao, H.T., Tsai, C.M., 2010. CO2 emissions, energy consumption and economic growth in BRIC countries. Energy Policy. doi:10.1016/j.enpol.2010.08.

Payne J. A survey of the electricity consumption-growth literature. Appl Energy 2010;87:723–31.

Pedroni P. 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bull Econ Stat ;61(4):5–49.

Pedroni, P., 2000. Fully modified OLS for heterogeneous cointegrated panels. In: Baltagi, B.H., Fomby, T.B., Hill, R.C. (Eds.), Advances in Econometrics, Vol. 15, Nonstationary Panels, Panel Cointegration and Dynamic Panels. JAI Press, Elsevier Sciences, Amsterdam.

Pedroni, P., 2001. Purchasing power parity tests in cointegrated panels. The Review of Economics and Statistics 83 (4), 727–731.

Pedroni, P., 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to PPP hypothesis: new results. Econometric Theory 20 (3), 597–627.

Phillips, Peter C.B. and Pierre Perron. "Testing for a Unit Root in Time Series Regression." *Biometrika* June 1988, 75, pp 335-346.

Runkle, D.E. 1987. Vector autoregressions and reality, *Journal of Business and Economic Statistics*, 5, 437-442.

Schwert, G William, 1989. " [Why Does Stock Market Volatility Change over Time?](http://ideas.repec.org/a/bla/jfinan/v44y1989i5p1115-53.html),"[Journal of Finance](http://ideas.repec.org/s/bla/jfinan.html), American Finance Association, vol. 44(5), pages 1115-53, December.

Shiu, A., Lam, L.P., 2004. Electricity consumption and economic growth in China. Energy Policy 30, 47– 54.

Sims, C. 1980. Macroeconomics and Reality. Econometrica 48, 1-49.

Sims, C., Stock, J., Watson, M., 1990. Inference in linear time series models with unit roots. Econometrica 58, 113– 144.

Soytas, U., Sari, R., 2003. Energy consumption and GDP: causality relationship in G-7 countries and emerging markets. Energy Economics 25, 33– 37.

Stern, D.I., 1993. Energy use and economic growth in the USA, a multivariate approach. Energy Economics, 15, 137– 150.

Stern, D.I., 2000. A multivariate cointegration analysis of the role of energy in the U.S. macroeconomy. Energy Economics 22, 267– 283.

Toda, H.Y., Phillips, P.C.B., 1993. Vector autoregressions and causality. Econometrica 61, 1367– 1393.

Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possibly integrated process. Journal of Econometrics 66 (1–2), 225–250.

Wang, P. 2003. Financial Econometrics. Routledge: NY.

Wolde-Rufael, Y., 2009. Energy consumption and economic growth: The experience of African countries revisited. Energy Economics, 31, 217-224.

Yoo, S.H., 2005. Electricity consumption and economic growth: evidence from Korea. Energy Policy 33, 1627– 1632.

Zachariadis, T., 2007. Exploring the relationship between energy use and economic growth with bivariate models: new evidence from G-7 countries. Energy Economics, 29, 1233– 1253.

1. It can be shown that OLS applied to each equation separately is asymptotically efficient (Harvey, 1989). [↑](#footnote-ref-1)