Relationship between U.S. energy consumption and income: evidence from non-linear Granger causality using geostatistical models

Arshia Amiri* [a, b], and Ulf-G Gerdtham [c, d, e]

[a] Department of Agricultural Economics, College of Agriculture, Shiraz University, Shiraz, Iran
[b] GREQAM CNRS – ORS PACA – INSERM U912, 23 rue Stanislas Torrents, F-13006 Marseille, France
[c] Department of Economics, Lund University
[d] Health Economics & Management, Institute of Economic Research, Lund University
[e] Centre for Primary Health Care Research, Lund University

Abstract

This paper introduces a new way of investigating nonlinear Granger causality between energy consumption and GDP in the United States over the period 1970-2005 using geostatistical models (kiriging and Inverse Distance Weight). In time series analysis most estimation of relationships and tests are typically based on linear estimators. Most classical cointegration methods and causality tests are based on OLS regresses. However the functional linear specification is not necessarily the most appropriate form. Then, in classical econometric methods there is not any estimator which has the capability to find the best functional form in the estimation. This paper breaks the ordinary rules in econometrics and makes use of time series with geostatistical methods. Geostatistical models investigate simultaneous linear and various nonlinear types of causality test, which lead to decrease the effects of choosing functional form in autoregressive model. This approach imitates the Granger definition and structure but improves it to have better ability to investigate nonlinear causality. Results of VEC and Improved-VEC (with geostatistical methods) are different. VEC confirms a uni-direction causal relation from GDP to energy consumption, but nonlinear investigation of VEC using geostatistical approaches proves the existence of bilateral causality in both of short- and long-run. The geostatistical analysing shows that there are Spherical and Exponential functions in nonlinear VEC structure instead of linear form.

Keywords: Granger causality; Energy consumption; GDP; Geostatistical model; Kiriging; Inverse distance weighting (IDW); Vector auto-regression; United States

*** Corresponding author. Tel.: +98 917 308 57 22; fax: +98 711 822 42 22.**
E-mail addresses: arshiaamirishiraz@gmail.com (A. Amiri).

1. Introduction

There is a rapidly growing literature on the interaction between energy use and economic development, with many analysts drawing policy conclusions on the basis of Granger causality tests that involve only energy and an economic variable (Zachariadis, 2007). Energy plays a huge role in the supply chain as it is both a final good for end-users as well as an input into the production processes of many industries and businesses. The decisions households and businesses must make regarding energy use are influenced by, and have implications for, short run changes in economic activity as well as longer term trends. For this reason, considerable attention has been placed on estimating the relationship between energy consumption and output. In the United States total energy expenditures account for more than 7% of Gross Domestic Product (Economic Report of the President, 2006). In fact, while petroleum comprises the largest imported energy source for the US, diversification of energy is generally considered important since it would lessen the dependence on foreign energy and thus dampen the effects of oil disruptions (Sari, Ewing and Soytas, 2008). Consequently, potential suppliers in the renewable sector, as well as in deregulated markets, may play a significant role in meeting the future energy requirements of the United States. Of course, newer technologies are developed and adopted as market signals dictate (Economic Report of the President, 2006).

Building on this, researchers have examined different countries over various time periods, using a number of different methodologies. Some of the studies that found evidence of Granger causality running from income to energy consumption include: Yu and Choi (1985) and Soytas and Sari (2003) for South Korea, Erol and Yu (1987a) for West Germany, Masih and Masih (1996) for Indonesia, Soytas and Sari (2003) for Italy,Wolde-Rufael (2005) for five African countries, Narayan and Smyth (2005) for Australia, and Lee (2006) for France, Italy and Japan. Additionally, Stern and Cleveland (2003) provide a review of the literature on the topic. In contrast, evidence of causality running from energy consumption to income has also been found. For example, Yu and Choi (1985) for Philippines, Erol and Yu (1987a) for Japan, Hwang and Gum (1992) for Taiwan, Stern (1993, 2000) for the US, Toda and Yamamoto (1995) for 11industrialized countries, Masih and Masih (1996) for India and Indonesia, Holtz-Eakin et al. (1998) for 18 developing countries, Asafu-Adjaye (2000) for Indonesia and India, Hondroyiannis et al. (2002) for Greece, Toman and Jemelkova (2003), for low-income countries Soytas and Sari (2003, 2006a) for Turkey, France, Germany, Japan and China, Ghali and El-Sakka (2004) for Canada, Wolde-Rufael (2004) for Shangai, Oh and Lee (2004) for South Korea, Altinay and Karagol (2004) for Turkey, Lee (2005) for eighteen developing countries, and Lee and Chang (2007) for 22 developed countries.

The few studies that did utilize disaggregate data include Yang (2000), Wolde-Rufael (2004), Sari and Soytas (2004), and Ewing, Sari and Soytas (2007) who highlight the importance of this new avenue of research. Thus, our approach is to utilize the disaggregate data in conjunction with a methodology that does not impose the additional restriction that the underlying series be integrated of the same order (Sari, Ewing and Soytas, 2008).

The literature on the energy consumption-real output relationship is mixed in the U.S. With respect to the four hypotheses[1] discussed, evidence supportive of the growth hypothesis has been provided by Akarca and Long (1979), Stern (1993, 2000), and Sari, Ewing, and Soytas (2008) whereas studies by Kraft and Kraft (1978), Erol and Yu (1989), Abosedra and Baghestani (1991), Murray and Nan (1992), Thoma (2004), Soytas and Sari (2006b), and Sari et al. (2008) support the conservation hypothesis. Research undertaken by Akarca and Long (1980), Yu and Hwang (1984), Yu and Choi (1985), Erol and Yu (1987b), Yu, Chow, and Choi (1988), Yu and Jin (1992), Cheng (1996), Murray and Nan (1996), Soytas and Sari (2003), Chontanawat, Hunt, and Pierse (2006, 2008), Soytas, Sari, and Ewing (2007), Chiou-Wei, Chen, and Zhu (2008), Narayan and Prasad (2008), Payne and Taylor (2008), Payne (2008b) are supportive of the neutrality hypothesis while studies by Glasure and Lee (1995, 1996), Zarnikau (1997), Lee (2006), and Mahadevan and Asafu-Adjaye (2007) lend support to the feedback hypothesis. As discussed by Zachariadis (2007) and Payne (2008a), the difference in results is due to the varying energy consumption and output measures, the econometric approaches, the presence of omitted variable bias, model specification, and the time horizons of the studies undertake (Bowden and Payne, 2008).
While the studies on the U.S. by Erol and Yu (1989) and Zachariadis (2007) examine aggregate energy consumption by sector or in the case of Thoma (2004) electricity usage by sector, these studies relied upon a bivariate analysis and thus suffered from omitted variable bias. The task of this study is to address the omitted variable bias by examining energy consumption and real GDP in total and by sector including measures of capital and employment (Bowden and Payne, 2008).
For testing the existence of a long-run or trendy relationship among energy use and GDP, the Durbin-Watson approach among others has to be applied. To meet this end, we analyse annual data for U.S., using VEC method developed by Engle and Granger (1987) with applying geostatistical models[2].
In time series analysis, all ordinary classical methods and tests apply linear estimators, such as OLS. If the null hypothesis of testing causality is not rejected using linear methods, our conclusion is that no causal linear relationship exists between the variables of interest. But it is essential to analyse and see if there exist nonlinear relationships between the variables during the time. This paper suggests a more general test using stronger nonlinear regressors like geostatistical methods in order to test the null hypothesis of causality with no particular reference to the functional form of the relationship.
In this paper, a new application of using geostatistical methods for testing causality in economics is suggested. In this improved method, geostatistical models are used for predicting VEC structures. There are some evidences[3] that results from this geostatistical methods which are more exact and supportive than OLS, such as, geostatistical models

[1] The papers try to test the causality in four energy using indexes (residential, industry, services, and transport) and GDP.

[2] Geostatistical methods are application methods in forecasting locatins and making map in water engineerig, environment, environmental pollution, mining, ecology, geology and geography.

[3] Geostatistical models are mentioned as strong nonlinear estimators on the empirical works in other fields. For empirical works see Van Kuilemberg et al. (1982), Voltz and Webster (1990), and Bishop and McBratney (2001).

which decreases the probable effects of choosing linear regressor, because they choose the best functional form between Linear, Linear to sill, Spherical, Exponential and Gaussian[4]. Geostatistical models have ability to mix different functional forms for Engle and Granger's structure, then, Engle-Granger method will be improved to have ability of investigating linear and nonlinear structures simultaneous[5].

On the empirical side, over 90% of Granger causality in energy economics was investigated in linear forms, and our paper is worthwhile to report an important issue in the fields of energy economics, economic growth, and policies toward energy use.

2. Methodology

Whether energy consumption cause GDP gains or losses, whether GDP cause gains energy consumption, or whether a two-way causal relationship exists between energy consumption and GDP can, in the end, be decided only empirically. Our investigation proceeded by studying the integration properties of the data, undertake a cointegrating analysis system, and examining Granger causality tests.

2.1. The data

The data are annual U.S. observations on GDP (constant 2000 US$) and energy use (kt of oil equivalent). Annual data on both variables is available from 1970 to 2005 from World Development Indicators 2008 software.

2.2. Testing for integration

In order to investigate the stationarity properties of the data, a univariate analysis of each time series (GDP and energy consumption) was carried out by testing for the presence of a unit root. Augmented Dickey-Fuller (ADF) *t*-tests (Dickey and Fuller, 1979) and Phillips and Perron (1988) $Z(t\hat{\alpha})$-tests for the individual time series and their first differences are shown in Table 1. The lag length for the ADF tests was selected to ensure that the residuals were white noise. ADF and PP tests computed using the first difference of *y*, and *ec* indicate that these tests are individually significant at the 5% level of significance. Therefore, GDP and energy consumption series are integrated processes of order one. This is a necessary step in order to test the cointegration of the variables.

Table 1
Tests for integration

Variables	ADF(C)	ADF(C+T)	PP(C)	PP(C+T)
y	3.91	-1.04	6.68	0.07
Δy	-3.66*	-3.69*	-3.55*	-4.73*
ec	-0.63	-2.48	-0.52	-2.04
Δec	-4.28*	-4.658*	-4.09*	-4.00*

4 see David (1977), Krige (1981), Cressie (1985, 1991), Isaaks and Srivastava (1989), and Hill et al. (1994).

5 There is no research which uses geostatical models to investigate nonlinear causality test. But there are some researches which suggest new nonlinear approaches in Granger causality, such as, Chen et al. (2004) and, Diks and Panchenko (2006).

Notes: Statistically significantly different from zero at the 0.05 significance level. The optimal lag used for conducting the ADF test statistic was selected based on an optimal criterion Akaike's Information Criterion (AIC), using a range of lags. While PP unit root tests determined by Newey-West with Bartlett kernel for bandwidth (see Newey and West, 1987).

2.3. Testing for cointegration

Using the concept of a stochastic trend, we may ask whether our series are driven by common trends (Stock and Watson, 1988) or, equivalently, whether they are cointegrated (Engle and Granger, 1987). A hypothesis on investigating cointegrating relationship and certain linear restrictions were tested using Durbin-Watson approach. The critical values for cointegration regression Durbin-Watson (CRDW) statistic have been computed by Sargan and Bhargava (1983) and by Engle and Granger (1987) which are 0.511, 0.386 and 0.322 for significant levels 0.01, 0.05 and 0.10 respectively. We find CRDW equal to 0.438 which reject the null hypothesis in 0.05 which confirms the existence of a long-run relationship between GDP and energy use in our sample.

2.4. Investigating Granger causality

Next, we first review the basic idea of Granger causality formulated for analysing linear systems and then propose a generalization of Engle Granger's idea to attractors reconstructed by geostatistical models coordinates.

2.4.1. Linear Granger causality test

Vector error correction (VEC) model is employed to detect the direction of the causality. Engle and Granger (1987) argued that if there is cointegration between the series, then the vector error correction model can be written as:

$$\Delta y_t = C_0 + \sum_{i=1}^{k} \beta_i \Delta y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta x_{t-1} + \rho_i ECT_{t-1} + u_t$$

$$\Delta x_t = C_0 + \sum_{i=1}^{k} \gamma_i \Delta x_{t-1} + \sum_{i=1}^{k} \zeta_i \Delta y_{t-1} + \eta_i ECT_{t-1} + \varepsilon_t \qquad (1)$$

where Δ is the difference operator; k, is the number of lags, α_s and ς_s are parameters to be estimated, $ECT_{,s-1}$ represents the error terms derived from the long-run cointegration relationship, $y_t = \alpha + \beta x_t + \varepsilon_t$, and u_t and ε_t the serially uncorrelated error terms.
Variable x_t is causing y_t, if we predict y_t better applying all available information (the optimum lags), than if the information apart from x_t had been used.

2.4.2. Extended Granger causality with geostatical models (kiriging and IDW)

The structure (1) may have nonlinear or contain both linear and nonlinear functional forms. Here we suggest estimating the structures of the Engle and Granger method combined with geostatistical models, since this may lead to a more careful estimation with new functions which can be used for investigating the causality. Here are the new shapes which will be used to estimate by kiriging and IDW. All f, h, g_i, l_i, m_i, n_i, q_i and p_j

are different functions, maybe linear or nonlinear[6] functions which are chosen as the best of them in kiriging and IDW.

$$\Delta y_t = f\left[\sum_{i=1}^{k} g_i(\Delta y_{t-1}) + \sum_{i=1}^{k} m_i(\Delta x_{t-1}) + n(ECT_{t-1})\right] + u_t$$

$$\Delta x_t = h\left[\sum_{i=1}^{h} l_i(\Delta x_{t-1}) + \sum_{i=1}^{k} P_i(\Delta y_{t-1}) + q(ECT_{t-1})\right] + \varepsilon_t \qquad (2)$$

2.5. Geostatistical analysis

In here, each variable such as independent and dependent, and its lags, are defined with a dimension in spatial structure. For example, if we want to determinate an unrestricted structure of VEC with one lag we face a 4D space for investigation with geostatistics approaches. In other word, in geostatistics the characteristics of location are the same as variables (exogenous and endogenous) in econometrics.

Geostatistics can be used to determine an unknown value, estimate endogenous variables, produce a map of parameters and confirm sampling process and make a more accurate sample. The first step is to analyze the spatial structure in which semivariogram is the essential tools. Describing and modeling are two parts of analysis structure for predicting semivariogram. The semivariogram is a mathematical description of the relationship between the variance of pairs of observations and the distance separating them (h or dependent variable), i.e. for a 3D space (one endogenous and two exogenous variables), it explains the relationships between population variance within a distance class (y-axis) according to the geographical distance between pairs of populations (x-axis). The semivariance is an autocorrelation statistic defined as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i + h) - Z(x_i)]^2 \qquad (3)$$

where: $\gamma(h)$ is the semivariance for interval distance class, $N(h)$is the whole number of sample pairs of observations separated by a distance h, $Z(x_i)$ is the measured sample value at point i, $Z(x_i + h)$ is the measured sample value at point i+h. Semivariance is evaluated by calculating g(h) for all possible pairs of points in the data set and assigning each pair to a lag or distance interval class h.

It can provide better resolved variograms when there are sufficient pairs of points at shorter separation distances. In Figure 6, there exists a shape of semivariance calculated in a 3D space where sill is $(C + C_0)$, the nugget variance (or constant amount) is $(C_0)$and the scale (or differences between nugget and observations separated by distance) is (C).

[6] Linear to sill, spherical, exponential, gaussian and so on.

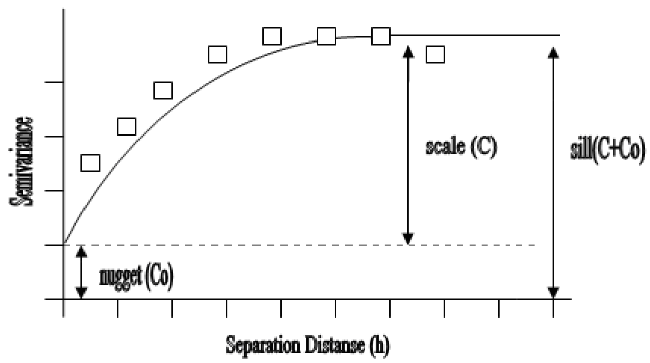

Figure 1: semivariance parameters in on surface.

In spatial structures we can calculate uncounted Semivariance in every degree. Collection of four semivariances in space is called variogram[7]. The next step is to analyse the variogram and find the type of variogram for our observation.
To create a 'trustworthy' variogram, different steps must be respected. Different lag distances have to be tested until a sufficient number of pairs to represent the model are found. Four representative groups of pairs are sufficient to represent a relevant variogram with a significant R^2 and a good 'nugget-to-sill' ratio. The effective lag distance cannot be more than half of the maximum distance between data (see Isaaks and Srivastava, 1989).
Burgos et al. (2006) explain that direct dependence has to be tested in the spatial autocorrelation. The isotropic (no directional dependence) or anisotropic (directional dependence) characteristic of the variogram has to be determined. If no anisotropy is found, it means that the value of the variable varies similarly in all directions and the semivariance depends only on the distance between sampling points.
At last the best variogram model (exponential, linear, etc.) and its parameters (nugget, sill, scale, range, etc.) have to be determined in order to validate the modeling of the spatial autocorrelation through the variogram's parameter optimization. The last step is to challenge between ordinary geostatistical methods (kriging and IDW) for predicting dependent variable.

2.5.1. Kriging

Kriging provides a means of interpolating values for points not physically sampled using knowledge about the underlying spatial relationships in a data set to do so. Variograms provide this knowledge. Kriging is based on regionalized variable theory and is superior to other means of interpolation because it provides an optimal interpolation estimate for a given coordinate location, as well as a variance estimate for the interpolation value (Gamma Design Software, 2004). In kriging, before determining the models, it is necessary to evaluate variogram to realize whether it is isotropic or anisotropic. The best way to evaluate anisotropy is to view the anisotropic semivariance surface (Semivariance Map), if anisotropic semivariance surface was symmetrical variogram would be isotropic, and if it was asymmetrical variogram would be anisotropic. The differences between variogram types, isotropic and anisotropics, lead to calculate same or various weights in

[7] In geostatistics it is ordinary to calculate four semivariances in 0, 45, 90 and 135 degrees.

space for kriging model. After the variogram estimation, the interpolation between the measurement points was carried out. To do this, ordinary kriging method was used to interpolate a great number of local scour maps of exogenous and endogenous variables[8]. Geostatistical and spatial correlation analyses of basic infiltration rate redistribution were performed with version 5.1 of GS^{+} software (Gamma Design Software, 2004).

2.5.2. Inverse distance weighting

Inverse Distance Weighting (IDW) is interpolation techniques in which interpolated estimates are made based on values at nearby spatial locations of our observation weighted only by distance from the interpolation location. IDW does not make assumptions about spatial relationships except the basic assumption that nearby points ought to be more closely related than distant points to the value at the interpolate location. Similar to kriging, inverse distance weighting (IDW), exactly implements the hypothesis that a value of an attribute at an unsampled location (variable) is a weighted average of known data points within other local neighborhoods surrounding the unsampled location (Robinson and Metternicht, 2006). In other word an improvement on simplicity giving equal weight to all samples is to give more weight to closet samples and less to those that are farthest away. One obvious way to do this is to make the weight for each estimated as follows:

$$\hat{Z}(x_0) = \frac{\sum_{i=1}^{n} Z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \tag{4}$$

Where x_0 is the estimation point and x_i are the data points within a chosen neighborhood. The weights (r) are related to distance by d_{ij}, which is the distance between the estimation point and the data points. The IDW formula has the effect of giving data points close to the interpolation point relatively large weights whilst those far away exert little influence.

3. Results

In this section results of the basic Granger causality test and generalization of Engle and Granger's test combined with geostatistical analysing coordinates are reported.

3.1. Results of linear Granger causality test with VEC

The empirical result using ordinary VEC confirms the existence of just one unidirectional causality relationship from GDP to energy consumption in long-run (Table 2). In order to find if any nonlinear relationship is found it is necessary to test nonlinear VEC in the following step.

Table 2
Results of causality tests based on VEC

Null hypotheses	Short run F-statistic	Long run F-statistic	Direction of short run	Direction of long run

[8] For more explanation of Kriging method see Isaaks and Srivastava (1989).

			causality	causality
GDP $\nRightarrow$ E.C.	0.53	4.56*	GDP $\nRightarrow$ E.C.	GDP $\Rightarrow$ E.C.
E.C. $\nRightarrow$ GDP	0.36	1.43	E.C. $\nRightarrow$ GDP	E.C. $\nRightarrow$ GDP

Notes: the lag lengths are chosen by using the AIC criterion; the statistics are F-statistic calculated under the null hypothesis of no causation. The coefficient of lag of error correction term is equal to zero is null hypothesis of long run causality test. $\nRightarrow$ denotes statistical insignificance and, hence fails to reject the null hypothesis of non-causality. $\Rightarrow$ denotes the rejection of the null hypothesis of non-causality. Significance level is as follows: *(5%) and **(1%).

3.1. Results of nonlinear Granger causality test with Improved-VEC

The result of Improved-VEC with geostatistical methods is different from VEC which verifies the existence of bi-directional causal relationships in both of short- and long-run between GDP and energy use (see Table 4). In half of estimation (see Table 3), spherical, and Exponential forms have better ability to regress the variables instead of the linear type. The Granger-Newbold test is applied to choose the best method between kriging and IDW. In 90% of relations, basing the results of Granger and Newbold (1976) test, geostatistical methods have a better ability of investigation. The best structure of Improved-VEC is available in Table 3.

Table 3
Best structure of geostatistical methods for testing causality based on Improved-VEC

Relations	Type of Variogram	Model of Variogram	Method
Δec_t is a function of Δy_{t-1} (unrestricted)	Anisotropic	Exponential	Kriging
Null hypotheses: $\Delta y_{t-1} = 0$	Isotropic	Linear	Kriging
Null hypotheses: $ECT_{t-1} = 0$	Isotropic	Linear	IDW
Δy_t is a function of Δec_{t-1} (unrestricted)	Isotropic	Linear	Kriging
Null hypotheses: $\Delta ec_{t-1} = 0$	Anisotropic	Spherical	IDW
Null hypotheses: $ECT_{t-1} = 0$	Isotropic	Spherical	Kriging

Notes: the Granger-Newbold test was estimated for choosing best method between IDW and ordinary kriging.

Table 4
Results of Results of causality tests based on Improved-VEC (with geostatistical methods)

Null hypotheses	Short run F-statistic	Long run F-statistic	Direction of short run causality	Direction of long run causality
growth $\nRightarrow$ E.C.	3134.31**	8.48**	growth $\Rightarrow$ E.C.	growth $\Rightarrow$ E.C.
E.C. $\nRightarrow$ growth	186.71**	9.78**	E.C. $\Rightarrow$ growth	E.C. $\Rightarrow$ growth

Notes: see Table 2.

4. Conclusions

There has been much interest in investigating causality between energy consumption and income. Over 90 percent in most of the studies cited the investigation Granger causality using the typical linear type. For testing Granger causality two methods were applied in this paper: VEC and Improved-VEC using geostatistical methods. The result of

Improved-VEC with geostatistical methods is different from VEC which verifies the existence of bi-directional causal relationships in both of short- and long-run between GDP and energy use. We find evidence that energy consumption and GDP move in tandem in the United States. This means that the U.S. economy is still on an unrestrained income path. This could lead to a more precise policy recommendation as to where energy conservation policies would not harm the economy (Lise and Van Montfort, 2007). In half of estimation, spherical, and Exponential forms have better ability to regress the variables instead of the linear type. In 90% of relations, geostatistical methods have a better ability of investigation instead of OLS in classical VEC structure. At least, we suggest economists applying other useful methods, such as artificial intelligences methods and genetic algorithms, to find higher and more satisfying results in time series analysis.

References

1. Abosedra, S., Baghestani, H., 1991. Newevidence on the causal relationship between United States energy consumption and gross national product. Journal of Energy and Development 14, 285–292.
2. Akarca, A.T., Long, T.V., 1979. Energy and employment: A time series analysis of the causal relationship. Resources and Energy 2, 151–162.
3. Akarca, A.T., Long, T.V., 1980. On the relationship between energy and GNP: A reexamination. Journal of Energy and Development 5, 326–331.
4. Altinay, G., Karagol, E., 2004. Structural break, unit root, and the causality between energy consumption and GDP in Turkey. Energy Economics 26, 985–994.
5. 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.
6. Bishop, T.F.A., McBratney A.B., 2001. A comparison of prediction methods for the creation of field-extent soil property maps. Geoderma 103, 149–160.
7. Bowden, N., Payne, J.E., 2008. The causal relationship between U.S. energy consumption and real output: A disaggregated analysis. Journal of Policy Modeling 31, 180–188.
8. Burgos, P., Madejon, E., Perez-de-Mora, A., Cabrera, F., 2006. Spatial variability of the chemical characteristics of a trace-element-contaminated soil before and after remediation. Geoderma 130 (1-2): 157–175.
9. Chen, Y., Rangarajan, G., Feng, J., Ding, M., 2004. Analyzing multiple nonlinear time series with extended Granger causality, Physics Letters, A, 324, 26–35.
10. Cheng, B.S., 1996. An investigation of cointegration and causality between energy consumption and economic growth. Journal of Energy and Development 21, 73–84.
11. Chiou-Wei, S.Z., Chen, C.F., Zhu, Z., 2008. Economic Growth and Energy Consumption: Evidence from Linear and Nonlinear Granger Causality. Energy Economics 30, 3063–3076.
12. Chontanawat, J., Hunt, L.C., Pierse, R., 2006. Causality between energy consumption and GDP: Evidence from 30 OEECD and 78 non-OECD countries. Surrey Energy Economics Discussion Paper Series 113.
13. Chontanawat, J., Hunt, L. C., 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.
14. Cressie, N., 1985. Fitting variogram models by weighted least squares. Mathematical Geology 17, 563–586.
15. Cressie, N.A.C., 1991. Statistics for Spatial Data. John Wiley, New York, USA.
16. David, M., 1977. Geostatistical Ore Reserve Estimation, Elsevier, Scientific Publishing Co., Amsterdam, The Netherlands.
17. Dickey, D. and Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of American Statisic Association 74, 427–431.
18. Diks, C., Panchenko, V., 2006. A new statistic and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics and Control 30, 1647–1669.
19. Economic Report of the President. United State Government Printing Office: Washington, DC; 2006.

20. Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation and testing. Econometrica 55, 251–276.
21. Erol, U., Yu, E.S.H., 1987a. On the causal relationship between energy and income for industrialized countries. Journal of Energy and Development 13, 113–122.
22. Erol, U., Yu, E.S.H., 1987b. Time series analysis of the causal relationships between US energy and employment. Resources and Energy 9, 75–89.
23. Erol, U., Yu, E.S.H., 1989. Spectral analysis of the relationship between energy consumption, employment and business cycles. Resources and Energy 11, 395–412.
24. Ewing, B.T., Sari, R., Soytas, U., 2007. Disaggregate energy consumption and industrial output in the United States. Energy Policy 35, 1274–1281.
25. Gama Design Software, 2004. GSp Version 5.1. Geostatistics for the Environmental Sciences, User's guide. Gama Design Software, LLC (pp. 160).
26. Ghali, K.H., El-Sakka, M.I.T., 2004. Energy use and output growth in Canada: a multivariate cointegration analysis. Energy Economics 26, 225–238.
27. Glasure, Y.U., Lee, A.R., 1995. Relationship between U.S. energy consumption and employment: Further evidence. Energy Sources 17, 509–516.
28. Glasure, Y.U., Lee, A.R., 1996. The macroeconomic effects of relative prices, money, and federal spending on the relationship between U.S. energy consumption and employment. Journal of Energy and Development 22, 81–91.
29. Granger, C.W.J., Newbold, P., 1976. The use of R^2 to determine the appropriate transformation of regression variables. Journal of Econometrics 4(3), 205–210.
30. Hill, T., Marquez, L., O'Connor, M. Remus, W., 1994. Artificial Neural Network Models for Forecasting and Decision Making. International Journal of Forecasting 10, 5–15.
31. Holtz-Eakin, D., Newey, W., Rosen, H., 1998. Estimating vector autoregression with panel data. Econometrica 56, 1371–1385.
32. Hondroyiannis, G., Lolos, S., Papapetrou, E., 2002. Energy consumption and economic growth: assessing the evidence from Greece. Energy Economics 24, 319–336.
33. Hwang, D.B.K., Gum, B., 1992. The causal relationship between energy and GNP: the case of Taiwan. The Journal of Energy and Development 16, 219–226.
34. Isaaks, E.H., Srivstava, R.M., 1989. Applied Goestatistics. New York Oxford University Press, pp. 257–259.
35. Kraft, J., Kraft, A., 1978. On the relationship between energy and GNP. Journal of Energy and Development 3, 401–403.
36. Krige, D.G., 1981. Lognormal-de Wijsian geostatistics for ore evaluation. South African Institute of Mining and Metallurgy Monograph Series. Geostatistics I. South Africa Institute of Mining and Metallurgy, Johannesburg, South Africa.
37. Lee, C.C., 2005. Energy consumption and GDP in developing countries: a cointegrated panel analysis. Energy Economics 27, 415–427.
38. Lee, C., 2006. The causality relationship between energy consumption and GDP in G-11 countries revisited. Energy Policy 34, 1086–1093.
39. Lee, C.C., Chang, C.P., 2007. Energy Consumption and GDP revisited: a panel analysis of developed and developing countries. Energy Economics 29, 1206–1223.
40. Lise, W., Van Montfort, K., 2007. Energy consumption and GDP in Turkey: Is there a co-integration relationship? Energy Economics 29, 1166–1178.
41. Mabit, L., Bernard, C., 2007. Assessment of spatial distribution of fallout radionuclides through geostatistics concept. Journal of Environmental Radioactivity 97, 206–219.
42. Mahadevan, R., Asafu-Adjaye, J., 2007. Energy consumption, economic growth and prices: A reassessment using panel VECM for developed and developing countries. Energy Policy 35, 2481–2490.
43. Masih, A., Masih, R., 1996. Energy consumption, real income and temporal causality: Results from a multi-country study based on cointegration and error-correction modeling techniques. Energy Economics 18, 165–183.
44. Murray, D.A., Nan, G.D., 1992. The energy and employment relationship: A clarification. Journal of Energy and Development 16, 121–131.
45. Murray, D.A., Nan, G.D., 1996. A definition of the gross domestic product-electrification interrelationship. Journal of Energy and Development 19, 275–283.

46. 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.
47. Narayan, P. K., Prasad, A., 2008. Electricity consumption-real GDP causality nexus: Evidence from a bootstrapped causality test for 30 OECD countries. Energy Policy 36, 910–918.
48. Newey, W., West, K., 1987. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
49. Oh, W., Lee, K., 2004. Energy consumption and economic growth in Korea: testing the causality relation. Journal of Policy Modeling 26, 973–981.
50. Payne, J.E., 2008a. Survey of the international evidence on the causal relationship between energy consumption and growth. Journal of Economic Studies, in press.
51. Payne, J.E., 2008b. On the dynamics of energy consumption and output in the U.S. Applied Energy, in press.
52. Payne, J. E., Taylor, J. P., 2008. Nuclear energy consumption and economic growth in the U.S.: An empirical note. Energy Sources, Part B: Economics, Planning, and Policy, in press.
53. Phillips, P., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335–346.
54. Robinson, T.P., Metternicht, G., 2006. Testing the performance of spatial interpolation techniques for mapping soil properties. Computer and Electronics in Agriculture 50, 97–108.
55. Sargan, J.H., Bhargava, A., 1983. Testing residual from least squares regression for being generated by Gaussian random walk. Econometrica 51, 153–174
56. Sari, R., Soytas, U., 2004. Disaggregate energy consumption, employment, and income in Turkey. Energy Economics 26, 335–344.
57. Sari, R., Ewing, B.T., Soytas, U., 2008. The relationship between disaggregate energy consumption and industrial production in the United States: An ARDL approach. Energy Economics 30, 2302–2313.
58. Soytas, U., Sari, R., 2003. Energy consumption and GDP: causality relationship in G-7 countries and emerging markets. Energy Economics 25, 33–37.
59. Soytas, U., Sari, R., 2006. Can China contribute more to the fight against global warming? Journal of Policy Modeling 28, 837–846.
60. Soytas, U., Sari, R., 2006b. Energy consumption and income in G7 countries. Journal of Policy Modeling 28, 739–750.
61. Soytas, U., Sari, R., Ewing, B.T., 2007. Energy consumption, income, and carbon emissions in the United States. Ecological Economics 62, 482–489.
62. Stern, D.I., 1993. Energy and economic growth in the USA, a multivariate approach. Energy Economics 15, 137–150.
63. Stern, D.I., 2000. A multivariate cointegration analysis of the role of energy in the US economy. Energy Economics 22, 267–283.
64. Stern, D.I., Cleveland, C.J., 2003. Energy and economic growth. Rensselaer Working Papers in Economics, pp. 0410.
65. Thoma, M., 2004. Electrical energy usage over the business cycle. Energy Economics 26, 363–385.
66. Toda, H.Y., Yamamoto, T., 1995. Statistical inference in vector autoregressions with possible integrated processes. Journal of Econometrics 66, 225–250.
67. Toman, M.A., Jemelkova, B., 2003. Energy and economic development: an assessment of the state of knowledge. Energy Journal 24 (4), 93–112.
68. Van Kuilemberg, J., De Gruitjer, J., Marsman, B., Bouma, J., 1982. Accuracy of spatial interpolation between point data on soil moisture supply capacity, compared with estimates from mapping units. Geoderma 27, 311–325.
69. Voltz, M., Webster, R., 1990. A comparison of kriging, cubic splines and classification for predicting soil properties from sample information. Journal of Soil Science 41, 473–490.
70. Wolde-Rufael, Y., 2004. Disaggregated energy consumption and GDP, the experience of Shangai 1952–1999. Energy Economics 26, 69–75.
71. Wolde-Rufael, Y., 2005. Energy demand and economic growth: the African experience 19 countries. Journal of Policy Modeling 27, 891–903.
72. Yang, H.Y., 2000. A note on the causal relationship between energy and GDP in Taiwan. Energy Economics 22, 309–317.
73. Yu, E.S.H., Choi, J.Y., 1985. The causal relationship between energy and GNP: an international comparison. Journal of Energy and Development 10, 249–272.

74. Yu, E. S. H., Hwang, B., 1984. The relationship between energy and GNP: Further results. Energy Economics 6, 186–190.
75. Yu, E.S.H., Chow, P.C.Y., Choi, J.Y., 1988. The relationship between energy and employment: A reexamination. Energy Systems and Policy 11, 287–295.
76. Yu, E.S.H., Jin, J.C., 1992. Cointegration tests of energy consumption, income, and employment. Resources and Energy 14, 259–266.
77. Zarnikau, J., 1997. A reexamination of the causal relationship between energy consumption and gross national product. Journal of Energy and Development 21, 229–239.
78. 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.