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Granger causality between energy use and economic growth in France with using geostatistical models

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Abstract

This paper introduces a new way for investigating linear and nonlinear Granger causality between energy use and economic growth in France over the period 1960_2005 with using geostatistical models (kiriging and IDW). This approach imitates the Granger definition and structure and also, improves it to have better ability for probe nonlinear causality. Results of both VEC and Improved-VEC (with geostatistical methods) are almost same. Both show the existence of long run unidirectional causality from energy consumption to economic growth. The geostatistical analyzing shows there are some Exponential functions in VEC structure instead of linear form.

Keywords: Granger causality; Energy consumption; GDP; Geostatistical model; France

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1. Introduction

Building on the relationship between energy consumption and income, 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: Kraft and Kraft (1978), Akarca and Long (1979), Yu and Hwang (1984), Yu and Choi (1985), Erol and Yu (1987b, 1989), Yu, Chow, and Choi (1988), Abosedra and Baghestani (1991), Murray and Nan (1992), Yu and Jin (1992), Stern (1993, 2000), Glasure and Lee (1995, 1996), Cheng (1996), Murray and Nan (1996), Zarnikau (1997), Soytas and Sari (2003, 2006b), Thoma (2004), Lee (2006), Chontanawat, Hunt, and Pierse (2006, 2008), Mahadevan and Asafu-Adjaye (2007), Zachariadis (2007), Soytas, Sari, and Ewing (2007), Sari et al. (2008), Chiou-Wei, Chen, and Zhu (2008), Narayan and Prasad (2008), Payne and Taylor (2008), Sari, Ewing, and Soytas (2008), Payne (2008a, 2008b), and Bowden and Payne (2008) for U.S., 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 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 empirical evidence from previous studies on this subject shows that the causal relationship between energy consumption and economic growth differs from country to country and overtime. In addition, previous studies have shown that the causality between the two variables may be sensitive to the choice of the energy consumption variable. Although the majority of the previous studies have found a direct causal relationship between the various proxies of energy consumption and economic growth, the literature regarding the possible neutrality between energy consumption and economic growth is growing in quantity and substance. The majority of the previous studies on the causality between energy consumption and economic growth have mainly used the residual based cointegration test associated with Engle and Granger (1987) and the maximum likelihood test based on Johansen (1988) and Johansen and Juselius (1990).Another thing, over 90% of Granger causality in energy economics was investigated in linear forms, except Amiri and Gerdtham (2011a) for the U.S. observation[1]. Our paper is worthwhile to report an important issue in the fields of energy economics, economic growth, and policies toward energy use.

[1] For finding emperical evidances of using Geostatistical models in time series analysis see Amiri and Gerdtham (2011b) in international trade and Amiri et al. (2011) in a health economics problem.

For testing the existence of a long-run or trend relationship among energy use and economic growth, the theory of cointegration developed by Pesaran and Shin (1995), Pesaran and Pesaran (1997), and Pesaran, Shin and Smith (2001) among others has to be applied. To this end, we analyze annual data for France, using the developed multivariate cointegration Engle and Granger (1987) approach with applying geostatistical models.
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[2] that results from this geostatistical methods which are more exact and supportive than OLS, such as, geostatistical models 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[3]. 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[4] (Amiri and Gerdtham, 2011a,b).

2. Methodology

In here we investigate cointegrating analysis, and examining Granger causality tests in order to find the direction of causality between energy consumption and economic growth.

2.1. The data

The data are annual France observations on economic growth (GDP %) and energy use (kt of oil equivalent). Annual data on both variables is available from 1960 to 2005 from World Development Indicators 2008.

2.2. Testing for integration

In order to investigate the stationarity properties of the data, a univariate analysis of each of the three time series (economic growth, 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. It is obvious from the ADF and Phillips and Perron (PP) tests that at conventional levels of significance. ADF and PP test computed using the first difference of *y*, and *ec* indicate that these tests are individually significant at the 1% level of

[2] 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).
[3] See David (1977), Krige (1981), Cressie (1985, 1991), Isaaks and Srivastava (1989), and Hill et al. (1994).
[4] 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).

significance. As differencing once produces stationarity, I conclude that the series *y* is integrated in order 0, *I*(0), and *ec* is integrated in order 1, *I*(1).

Table 1, tests for integration

Variables	ADF(C)	ADF(C+T)	PP(C)	PP(C+T)
y	-3.262	-4.577*	-3.084	-4.571*
Δy	-6.799*	-6.731*	-14.934*	-16.395*
ec	-1.620	-3.554	-1.649	-2.059
Δec	-6.634*	-6.819*	-6.634*	-6.819*

[a]*Notes*. Statistically significantly different from zero at the 0.01 significance level. The optimal lag used for conducting the ADF test statistic was selected based on an optimal criterion Akaike's FPE, using a range of lags. while PP unit root tests determined by Newey-West with Bartlett kernel for bandwidth (see Newey and West, 1987).

Therefore, economic growth and energy consumption series are integrated processes of order zero and one. This is a necessary step in order to test the cointegration of the variables.

2.4. 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 with using ARDL which proposed by Pesaran and Shin (1995), Pesaran and Pesaran (1997), and Pesaran, Shin and Smith (2001) (see Pesaran and Pesaran (1997) for more details and an application using MICROFIT econometric software.).
Pesaran critical values are chosen, which are *I*(0) = 7.934 and *I*(1) = 7.815 for using intercept no trend in 1% probability (see Pesaran and Pesaran (1997), Pesaran, Shin and Smith (2001)), for testing the existence of cointegration relationships. The calculated F statistic were 8.3105 which were more than both Pesaran critical values that rejects null hypothesis which says there is not a long run relationship between variables. ARDL (Autoregressive Distributed Lag) system was determined by minimizing the Akaike Information Criterion (AIC). The results support the existence of a cointegrating relation with growth-energy consumption (y=6.3986 - 0.1998E-4*ec).

2.5. Investigating Granger causality

In this section we will first review the basic idea of Granger causality formulated for analyzing linear systems and then propose a generalization of Engle Granger's idea to attractors reconstructed with geostatistical models coordinates.

2.5.1. Linear Granger causality test

In order to describe this part we reference the paper of Saytos and Sari (2003) in Energy Economics on page 35. Cointegration implies the existence of Granger causality. However, it does indicate the direction of the causality relationship. Therefore, the 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

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

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

where Δ is the difference operator; k, is the numbers 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.
In each equation, the change in the dependent variable is caused not only by the lag, but also by the previous period's disequilibrium level. The joint significance indicates that each dependent variable is responding to short-term shocks to the stochastic environment; the long-run causality can be tested by looking at the significance of the speed of adjustment, which is the coefficient of the error correction term. The significance indicates that the long-run equilibrium relationship is directly driving the dependent variable (Yoo, 2006).The results of the Granger causality tests of the model are reported in Table 2, which also reports the tests used to choose the lag lengths.

2.5.2. 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[5] functions which are chosen as the best of them in kiriging and IDW.

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

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

2.6. 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:

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

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

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).

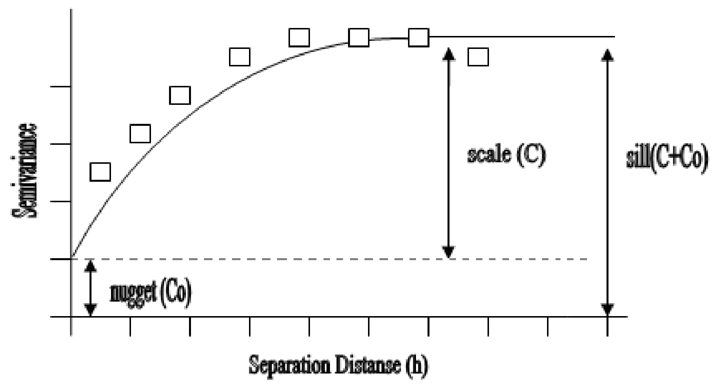

Figure 1: semivariance parameters in on surface.

In spatial structures we can calculate uncounted Semivariance in every degree. Collection of four semivariances in space is called variogram[6]. 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.

2.6.1. Ordinary 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

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

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 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[7]. Geostatistical and spatial correlation analyses of basic infiltration rate redistribution were performed with version 5.1 of GS^{+} software (Gamma Design Software, 2004).

2.6.2. 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 we will first attention to results of the basic Granger causality formulated for analyzing linear systems and then probe a generalization of Engle and Granger's idea to attractors reconstructed with geostatistical analyzing coordinates.

3.1. Results of linear Granger causality test with VEC

The empirical results with using ordinary VEC suggest that energy consumption stimulates economic growth of France in long run and short run. The empirical results confirm a high unidirectional causality from energy consumption to economic growth in long run. Results are available in Table 2.

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

Table 2, results of causality tests based on VEC

Null hypotheses	Short run F-statistic	Long run F-statistic	Direction of short run causality	Direction of long run causality
growth $\nRightarrow$ E.C.	0.036260	0.884880	growth $\nRightarrow$ E.C.	growth $\nRightarrow$ E.C.
E.C. $\nRightarrow$ growth	1.507560	16.79796**	E.C. $\nRightarrow$ growth	E.C. $\Rightarrow$ growth

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 ran causality test and the coefficient of lag of exogenous variable is equal to zero is null hypothesis of short ran 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

Results of both VEC and Improved-VEC (with geostatistical methods) are almost same (Table 4). Both show the existence of long ran unidirectional causality from energy consumption to economic growth, but F-statistic of VEC shows a long ran relationship from energy consumption to economic growth in 1% probability of error, which F-statistic of Improved-VEC for these relationships is lower than VEC (shows in 5% error probability). In some relationships, Exponential form is investigated instead of linear type. The Granger-Newbold (1976) test is applied to choose best method between kriging and IDW 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	Linear	IDW
Null hypotheses: $\Delta y_{t-1} = 0$	Isotropic	Linear	IDW
Null hypotheses: $ECT_{t-1} = 0$	Isotropic	Exponential	IDW
Δy_t is a function of Δec_{t-1} (unrestricted)	Anisotropic	Linear	IDW
Null hypotheses: $\Delta ec_{t-1} = 0$	Anisotropic	Linear	IDW
Null hypotheses: $ECT_{t-1} = 0$	Anisotropic	Exponential	Kriging

Notes: the Granger-Newbold test was estimated for chosing 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 ran F-statistic	Long ran F-statistic	Direction of short run causality	Direction of long run causality
growth $\nRightarrow$ E.C.	0.175246	0.394256	growth $\nRightarrow$ E.C.	growth $\nRightarrow$ E.C.
E.C. $\nRightarrow$ growth	0.000000	6.478308*	E.C. $\nRightarrow$ growth	E.C. $\Rightarrow$ growth

Notes: see table 2.

4. Conclusions

There has been much interest in investigating causality between energy consumption and economic growth. Over 90 percent in most of the studies cited the investigation Granger causality with using linear type. For testing the Granger causality two methods were applied; VEC and Improved VEC with geostatistical methods. Results from these two methods were almost same. Both show the existence of long run unidirectional causality from energy consumption to economic growth. In some relationships, Exponential form is investigated instead of linear type.

In summary, this study provides some insights into the relationship between energy consumption and economic growth in the examination of energy consumption by sector that may otherwise be masked by an analysis of aggregate energy consumption. Future research on the relationship between the various disaggregated energy sources within each sector and real GDP growth may shed additional insight on the relative impact of energy consumption on the economy as well as assist in the development of a more prudent and effective energy and environmental policies for the France.

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