Electricity Consumption and Economic Growth: Evidence from Spain

Aitor Ciarreta[a], Ainhoa Zarraga[b*]

[a] *Department of Economic Analysis II, University of the Basque Country, Lehendakari Agirre 83, Bilbao 48015, Spain*

[b] *Department of Applied Economics III, University of the Basque Country, Lehendakari Agirre 83, Bilbao 48015, Spain*

Abstract

The paper investigates linear and nonlinear causality between electricity consumption and economic growth in Spain for the period 1971-2005. We use the methodology of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). We also apply the standard Granger causality tests in a VAR for the series in first differences to achieve stationarity. The results are similar with both methodologies, which shows their robustness. We find unidirectional linear causality running from real GDP to electricity consumption. By contrast, we find no evidence of nonlinear Granger causality between the series in either direction.

JEL classification: C32, Q40

Keywords: Electricity consumption; economic growth; causality.

*Corresponding author. Tel.: +34-94-601-7033; fax: +34-94-601-3754.

E-mail address: ainhoa.zarraga@ehu.es (A. Zarraga).

1 Introduction

The interest of studying of the relationship between energy consumption and economic growth arises from the need to understand the complex links between the two variables. Such en understanding is basic to regulators and investors in deregulated electricity markets, in order to design a system that ensures reliability and efficiency.

The purpose of our study is twofold. First, we extend the analysis of the dynamic linear relationship between electricity consumption and economic growth to the Spanish economy for the period 1971 to 2005. To our knowledge there are no studies of this nature for Spain. Second, we explore the possible existence of links more complex than linear ones to study non-linear dynamic relations.

Energy economics literature has made significant theoretical contributions on the causal effects of energy price fluctuations on economic growth but it lacks linkages between energy consumption and economic growth. For that reason the area has been subjected to active empirical research over the past two decades. At a disaggregated level, electricity consumption is also of special interest. Most findings conclude that there is a strong relationship between the two variables. Ferguson et al. (2000) find correlation between electricity use and wealth creation in 100 developing countries, and the correlation is stronger between electricity use and wealth than between total energy use and wealth. However, even though that correlation may be present, it does not necessarily imply a causal relationship in either direction. Causality tests can provide useful information on whether knowledge of past electricity consumption movements improves forecasts of movements in economic growth and vice versa.

We can classify the studies to date into four groups. First, a large number of studies find unidirectional causality running from electricity consumption to GDP. Studies worthy of mention include those by Altinay and Karagol (2005) for Turkey, which find strong evidence for the period 1950-2000, Lee and Chang (2005) in Taiwan for the period 1954-2003, Shiu and Lam (2004) in China for 1971-2000, and Soytas and Sari (2003) for Turkey, France, Germany and Japan. Second come those that find unidirectional causality running from economic growth to electricity consumption. These include Ghosh (2002) for India in 1950-1997, Fatai et al. (2004) for New Zealand and Australia in 1960 to1999, and Hatemi and Irandoust (2005) for Sweden in 1965-2000. A third group comprises studies that find bi-directional causality. This include Soytas and Sari (2003) for Argentina, Oh and Lee (2004) for Korea in 1970-1999 and Yoo (2005) also for Korea in 1970-2002. And the last group comprises studies that find no causal linkages between energy, or even electricity, consumption and economic growth, such as Cheng (1995) and Stern (1993) for the USA in 1947-1990. Wolde-Rufael (2006) finds a mixture of results for the period 1971-2001, but considering that electricity consumption accounts for less than 4% of total energy consumption, the results are less robust.

These studies focus primarily on developing economies. The unidirectional causality between electricity consumption and economic growth seems to be more consistent for these countries. The conclusion is that a reliable increasing electricity supply is required to meet growing electricity consumption, and as a result to sustain paths of economic growth. Therefore, a further implication is that energy conservation policies may come into conflict with economic growth.

Tests for unit roots, cointegration and linear Granger-causality based on vector autorregressive models are used. Additionally, we test for nonlinear Granger causality between the data series using a nonparametric method.

The rest of the paper is structured as follows. Section 2 presents the methodology. Section 3 describes the data and presents the results of the Granger causality tests. Section 4 concludes.

2 Methodology

The idea of causality is that the cause precedes the effect, that is, if an event Y is the cause of another event X, then Y should precede X. Causality in the sense defined by Granger (1969) exists when lagged values of a variable, say Y, have explanatory power on another variable X. Therefore, if Y Granger causes X the prediction error of current X declines when lagged values of Y are used.

In order to test for linear Granger causality between two series, Y_1 and Y_2, autoregressive or vector autoregressive (VAR) models are usually estimated:

$$\begin{aligned} Y_{1t} &= \nu_1 + B_{11}(L)Y_{1t} + B_{12}(L)Y_{2t} + U_t \\ Y_{2t} &= \nu_2 + B_{21}(L)Y_{1t} + B_{22}(L)Y_{2t} + W_t \end{aligned} \tag{1}$$

where $B_{ij}(L)$ for $i, j = 1, 2$ are lag polynomials of order p.

Tests of causality can be conducted by testing whether some parameters of the lag polynomials of equations (1) are jointly zero, for which a simple F test is applied. However, this methodology requires the series to be stationary since using non-stationary data can yield spurious causality results (see Sims et al. (1990) or Toda and Phillips (1993)).

If series are non-stationary they may also be cointegrated, that is, there may be a stationary relationship between them even though they are individually non-stationary. In that case, a bivariate model containing error correction mechanism terms may be used. Cointegration guarantees the existence of Granger causality between the series in at least one direction. By contrast, if series are integrated but not cointegrated, causality tests may be implemented by estimating a VAR for the differenced series to achieve stationarity so conventional asymptotic theory is valid for hypothesis testing.

Thus, it seems natural to test the unit roots of series and if they are integrated of the same order, then test for cointegration. Conventional unit root tests such as Augmented Dickey-Fuller (Dickey and Fuller (1979)) or Phillips-Perron (Phillips and Perron (1988)) are usually applied to single series. Unfortunately, the power of standard unit root tests is very low against the alternative hypothesis of stationarity.

Some other unit root tests have been developed in which the alternative hypothesis is a trend-stationary process allowing for the presence of a one-time change. Perron (1989) shows that the standard tests of a unit root against the alternative hypothesis of a trend-stationary process cannot reject the existence of a unit root if the true data generating mechanism is a trend-stationary process which contains a one-time break. However, the test he proposes treats the time of the break as exogenous which means that it has to be known a priori. Zivot and Andrews (1992) develop a modified version that allows for a trend-stationary process with a one-time break in the trend at an unknown point in time under the alternative hypothesis. Later, Perron

(1997) proposes a test in which the break point is estimated endogenously. However, several studies (see Weber (2001) and Lee and Strazicich (2001)) have criticized the lag length selection procedure adopted by Zivot and Andrews (1992) and Perron (1989) and show that inference could be affected. As far as we know, there is no conclusive literature establishing the best method for selecting lag length in the regression equation or estimating the break point. However, the results are crucial since incorrect decisions will affect inference about the order of integration of series.

If series are integrated of the same order, then the test for cointegration of Engle and Granger (1987), Johansen (1988) or Johansen and Juselius (1990) are typically applied. But tests for cointegrating ranks are sensitive to nuisance parameters in finite samples.

Therefore, this testing sequence prior to the estimation of the VAR model in which inference is conducted could present severe biases and affect the inference procedure.

As a possible solution, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) propose a method of estimating a VAR for series in levels and test general restrictions on the parameter matrices even if the series are integrated or cointegrated. They develop a modified version of the Granger causality test which involves a modified Wald test in an intentionally augmented VAR model. Once the optimal order of the VAR process, p, is selected, Toda and Yamamoto (1995) propose estimating a $VAR(p + d_{max})$ model where d_{max} is the maximal order of integration that we suspect might occur in the true generation process. Linear or nonlinear restrictions on the first p coefficient matrices of the model can therefore be tested using standard Wald tests ignoring the last d_{max} lagged vectors of the variables. Dolado and Lütkepohl (1996) also propose estimating an augmented VAR with the difference that they add only one lag to the true lag length of the model. One estimates the VAR(p+1) model and perform the standard Wald tests ignoring the last lag of the vector.

The advantage of these tests is that they are computationally relatively simple and do not require pretesting for integration or cointegration of the data series. These tests are especially attractive when one is not sure whether series are stationary or integrated of order one. Altinay and Karagol (2005) and Wolde-Rufael (2006), among others, use this type of methodology to test for causality between electricity consumption and economic growth for several countries.

In this context, we proceed as follows. First, we follow the methodology proposed by Dolado and Lütkepohl (1996) and Toda and Yamamoto (1995) to test for linear causality between Spanish electricity consumption and real GDP avoiding the possible pretest biases due to the traditional tests for the order of integration and cointegration of the series. Second, we also follow the traditional steps to test for causality, namely we test for unit roots in the data series using the Augmented Dickey-Fuller and Phillips-Perron unit root tests where the null hypothesis is the existence of a unit root in the series. As we find evidence that the series are integrated of order one, we proceed to test for cointegration applying the approach of Pesaran et al. (2001) based on a bounds testing procedure. This method makes it possible to draw a conclusive inference about cointegration with no need to know the order of integration of the series if the computed F-statistic calculated from an unrestricted error correction model falls outside the critical bounds. Once we determine that the data series are integrated of order one but not cointegrated, we proceed to test for causality using the traditional Granger causality tests in a VAR model for the series in first differences. Then we compare the results of causality tests obtained by the two methods and check their robustness.

One problem of linear Granger causality tests is that they can have low power uncovering nonlinear causal relations. Brock (1991) illustrates the problem with a bivariate nonlinear model in which one series depends nonlinearly on a past value of the other series but linear causality tests incorrectly conclude that there is no lagged dynamic relation between the series. Baek and Brock (1992) propose a nonparametric method for testing for nonlinear causal relations that, by construction, cannot be detected by traditional linear Granger causality tests. This method has been used in various fields (Baek and Brock (1992), Jaditz and Jones (1993), Hiemstra and Jones (1994), Hiemstra and Kramer (1997) and Zarraga (1998), among others) and in some cases a nonlinear Granger causality between the series studied has been found.

In this paper we follow the test proposed by Hiemstra and Jones (1994) based on the nonparametric method of Baek and Brock (1992) to test for nonlinear Granger causality. The test is applied to the two residual series from the estimated VAR model. The idea is that once the linear predictive power is captured by a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered as nonlinear predictive power.

A detailed explanation of the methodology used to test for nonlinear causality is presented in Appendix A.

3 Data and empirical results

3.1 Data

The data used in this study correspond to annual observations for the period 1971 to 2005. The electricity consumption data, expressed in terms of gigawatt hours (GWh), are obtained from the electricity system operator *Red Eléctrica Española (REE)*. REE runs the entire electricity system to ensure reliability and publishes monthly bulletins with the levels of consumption for the entire system including islands and outlying territories. Real GDP is measured in constant 1986 prices and denominated in millions of euros, taken from *Instituto Nacional de Estadística, INE*, which coordinates all statistical services for the public administration.

The data are transformed into natural logarithms denoted as LEC and LGDP, respectively. Plots of the series are presented in Figures 1 and 2 respectively.

FIGURE 1

FIGURE 2

As can be seen there is an increasing trend in both variables. Real GDP exhibits two periods of negative growth in 1973 and 1993, whereas electricity consumption maintains an increasing path that except 1993, when there is zero growth.

3.2 Dolado and Lütkepohl's approach

To apply the Dolado and Lütkepohl (DL) (1996) test explained above, we first select the lag length, p, of an unrestricted VAR(p) using Akaike's criterion. The optimum selected lag is 2, so we estimate the following VAR model by OLS setting $p = 3$ lags, that is, the optimum number of lags plus one.

$$\begin{bmatrix} LEC_t \\ LGDP_t \end{bmatrix} = \begin{bmatrix} \nu_1 \\ \nu_2 \end{bmatrix} + \begin{bmatrix} a_{11,1} & a_{12,1} \\ a_{21,1} & a_{22,1} \end{bmatrix} \begin{bmatrix} LEC_{t-1} \\ LGDP_{t-1} \end{bmatrix} +$$

$$\begin{bmatrix} a_{11,2} & a_{12,2} \\ a_{21,2} & a_{22,2} \end{bmatrix} \begin{bmatrix} LEC_{t-2} \\ LGDP_{t-2} \end{bmatrix} + \begin{bmatrix} a_{11,3} & a_{12,3} \\ a_{21,3} & a_{22,3} \end{bmatrix} \begin{bmatrix} LEC_{t-3} \\ LGDP_{t-3} \end{bmatrix} + \begin{bmatrix} U_t \\ W_t \end{bmatrix} \quad (2)$$

The null hypothesis that real GDP does not strictly Granger cause electricity consumption is rejected if the coefficients $a_{12,1}$ and $a_{12,2}$ are jointly significantly different from zero, whereas the null hypothesis that electricity consumption does not strictly Granger cause real GDP is rejected if the coefficients $a_{21,1}$ and $a_{21,2}$ are jointly significantly different from zero. Bidirectional causality exists if Granger causality runs in both directions. These tests are conducted with an F-statistic and the results are presented in Table 1.

TABLE 1

As can be seen, for a probability value of 0.10 there is evidence of unidirectional Granger causality running from Spanish real GDP to electricity consumption, whereas there is no evidence of Granger causality running in the opposite direction.

3.3 Standard Granger causality test

In order to apply the traditional methodology to test for linear Granger causality, we first determine the order of integration of the series by applying the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests to the logs of the data series. Table 2 shows the results of the ADF tests[1]. As can be seen, we cannot reject the null hypothesis of unit root for both series in levels, while the t-statistics for the series in first differences are smaller than the corresponding critical values. Thus, we conclude that electricity consumption and real GDP series are integrated of order one.

TABLE 2

As we find evidence that both series are integrated of order one[2], we proceed to test for cointegration, that is, we test whether there exists a linear combination of the individually non-stationary series which is stationary itself. As mentioned above, we use the Pesaran et al. (2001) method based on the following unrestricted error correction model:

$$\Delta LEC_t = \alpha_1 + \sum_{i=1}^{m} \beta_{1i} \Delta LEC_{t-i} + \sum_{i=1}^{m} \delta_{1i} \Delta LGDP_{t-i} + \eta_{11} LEC_{t-1} +$$

$$\eta_{12} LGDP_{t-1} + u_{1t} \tag{3}$$

$$\Delta LGDP_t = \alpha_2 + \sum_{i=1}^{m} \beta_{2i} \Delta LEC_{t-i} + \sum_{i=1}^{m} \delta_{2i} \Delta LGDP_{t-i} + \eta_{21} LEC_{t-1} +$$

$$\eta_{22} LGDP_{t-1} + u_{2t} \tag{4}$$

and test for the joint significance of the lagged variables in levels in each equation separately using the F-test. The null hypothesis of no cointegration is defined as $H_0 : \eta_{11} = \eta_{12} = 0$ in equation (3) and $H_0 : \eta_{21} = \eta_{22} = 0$ in equation (4). Table 3 presents the results of the test as Pesaran et al. (2001) for cointegration. Under the null of no cointegration, the asymptotic distribution of the statistic is non-standard. Pesaran et al. (2001) provide two sets of asymptotic critical values, one when all regressors are purely integrated of order one and the other when they are purely stationary. If the F-statistic falls outside the critical bounds, a conclusive inference can be drawn with no need to know the order of integration of the series. For the case of Spanish GDP and electricity consumption the F-statistics computed are bellow the lower critical value, therefore the null hypothesis of no cointegration between the data series cannot be rejected[3].

TABLE 3

As we find that the series are integrated of order one but not cointegrated, the Granger causality tests may be implemented by estimating a VAR in the first differences of the series to achieve stationarity so that the conventional asymptotic theory is valid for hypothesis testing. We estimate the following VAR for the differenced series[4]:

$$\Delta LEC_t = \nu_1 + \gamma_{11}\Delta LEC_{t-1} + \gamma_{12}\Delta LGDP_{t-1} + U_t \tag{5}$$

$$\Delta LGDP_t = \nu_2 + \gamma_{21}\Delta LEC_{t-1} + \gamma_{22}\Delta LGDP_{t-1} + W_t \tag{6}$$

and test the null hypothesis $H_0 : \gamma_{12} = 0$ that LEC does not Granger cause LGDP and $H_0 : \gamma_{12} = 0$ that LGDP does not Granger cause LEC with a simple F-statistic. Results of the causality tests are presented in Table 4. The results indicate again that, for a probability value of 0.10, there is unidirectional causality running from Spanish real GDP to electricity consumption.

TABLE 4

Therefore, we obtain the same results using two methodologies: the traditional Granger causality test in a VAR for the series in first differences to achieve stationarity and the methodology proposed by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). This shows the robustness of the results to different methodologies. Also, Altinay and Karagol (2005) prove the robustness of causality results for Turkey in the period 1950-2000 by using three different methodologies: the Dolado and Lütkepohl (1996) test, the standard Granger causality test to the detrended series and the standard Granger causality test based on the differenced data. However, they find strong evidence for unidirectional causality running from electricity consumption to real GDP.

3.4 Nonlinear Granger causality test

As we study linear causality using two different methodologies, we apply nonlinear Granger causality tests to the standardized residual series in the estimated VAR models for those two methodologies, namely, a VAR with 3 lags for the series in levels and a VAR with 1 lag for the first differenced series.

The null hypothesis is the absence of nonlinear causality. Taking into account the size of the data series we select $m = 1$ lead and $Lu = Lw = 1$ lag and, following Hiemstra and Jones (1994), we select $e = 0.5^5$. We calculate the corresponding standardized statistic and evaluate it with right-tailed critical values.

The results of the nonlinear causality tests are reported in Table 5, where it can be seen that there is no evidence of nonlinear Granger causality between electricity consumption and GDP series in either direction. The results when the test is applied to the residuals of the estimated VAR(3) for the series in levels are similar to those for the residuals of the estimated VAR(1) for the first differenced series, which proves their robustness of the results, as was the case for the tests of linear causality.

TABLE 5

This result is not inconsistent with the finding of unidirectional linear causality since the methodology used is designed to detect nonlinear causal relations that cannot be detected by traditional linear Granger causality tests.

4 Conclusions

The paper studies the dynamic relationship between electricity consumption and real GDP in Spain for the period 1971 to 2005. We use linear Granger causality tests in a VAR for the differenced series, and also the test proposed by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). We find the same results using both types of test. Namely, there is unidirectional causality running from GDP to electricity consumption.

The result is along the same lines as studies for some countries in the European Union, such as Sweden, and countries as far away as Australia and

New Zealand (Fatai et al. (2004)).

On the other hand, we find no evidence of nonlinear causality between the series in either direction. These results indicate that past values of electricity consumption improve forecasts of movements in economic growth, but they do so in a linear manner and therefore the causal relationship between the series is not abrupt or complex enough to be nonlinear. This result may arise because we use yearly observations. Thus, it is very difficult to obtain more complex relationships between the two variables.

Finally, we want to emphasize the importance of this type of studies in terms not only of the amount of literature that has been published, but also of how policy makers have used them. In particular, the US Department of Energy requested a report in 1986 (Committee on Electricity in Economic Growth (1988)) on the relationship between economic growth and electricity to design development programs and suitable incentives for the private sector. We believe this is also necessary in Spain to meet the challenges in the near future, such as the Kyoto Protocol on CO_2 emissions, the use of more efficient generation technologies that do not hinder the target of sustained economic growth.

Acknowledgements

Aitor Ciarreta would like to acknowledge the financial support provided by Ministerio de Educación y Ciencia under research grant BEC2003-02084. Ainhoa Zarraga would like to acknowledge the financial support provided by Ministerio de Educación y Ciencia under research grant SEJ2004-04811. The authors would like to thank Marta Regúlez for her valuable comments and all seminar participants at the II Meeting of the Asociación Española para la Economía Energética at Oviedo 2007.

Notes

[1]For the sake of simplicity, we only present the ADF test results. The results of the PP unit root test are similar and are available upon request.

[2]We also use the Zivot and Andrews (1992) method to test for a unit root against the alternative hypothesis of a trend-stationary process with a one time break in the trend at an unknown point in time. However, the results are not conclusive, since changing the lag length selection procedure affects inference. The results of the tests are available upon request.

[3]The Johansen greatest eigenvalue and trace tests for cointegration have also been applied, but the results do not change.

[4]The lag length is chosen by using the Akaike's information criterion for a maximum of 4 lags.

[5]We also use a scale parameter value of 1.5 but these results are not reported since they are similar to those reported for $e = 0.5$. The complete set of results is available from the authors upon request.

References

Altinay, G., Karagol, E., 2005. Electricity consumption and economic growth: Evidence from Turkey. Energy Economics. 27, 849-856.

Baek E., Brock, W., 1992. A general test for nonlinear Granger causality: Bivariate model. Working Paper. Iowa State University and University of Wisconsin, Madison.

Brock, W., 1991. Causality, chaos, explanation and prediction in economics and finance, in: Casti, J., Karlqvist, A. (Eds.), Beyond Belief: Randomness, Prediction and Explanation in Science, CRC Press, Boca Raton, Fla.

Cheng, B.S., 1995. An Investigation of Cointegration and Causality between Energy Consumption and Economic Growth. Journal of Energy and Development. 21, 73-84.

Committee on electricity in economic growth, 1988. Electricity in Economic Growh, a report prepared by the Committee on electricity in economic growth. National Academic Press, Washington D.C.

Dickey, D., Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association. 74, 427-431.

Dolado, J.J., Lütkepohl, H., 1996. Making Wald test work for cointegrated VAR systems. Econometric Reviews. 15, 369-386.

Engle, R., Granger, C., 1987. Cointegration and error correction: representation, estimation, and testing. Econometrica. 55, 257-276.

Fatai, K., Oxley, L., Scrimgeour, F.G., 2004. Modelling the causal relationship between energy consumption and GDP in New Zealand, Australia, India, Indonesia, The Philippines and Thailand. Mathematics and Computers in Simulation. 64, 431-445.

Ferguson, R., Wilkinson, W., Hill, R., 2000. Electricity use and economic development. Energy Policy. 28, 923-934.

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

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

Hatemi, A., Irandoust, M., 2005. Energy Consumption and Economic Growth in Sweden: A Leveraged Bootstrap Approach, 1965-2000. International Journal of Applied Econometrics and Quantitative Studies. 4, 1-20.

Hiemstra, C., Jones, J.D., 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation. Journal of Finance 49. 1639-1664.

Hiemstra, C., Kramer, C., 1997. Nonlinear and endogeneity in macro-asset pricing. Studies in Nonlinear dynamics and Econometrics. 2, 61-76.

Jaditz, T., Jones, J., 1993. Granger causality between the consumer and wholesale price indices. Bureau of Labor Statistics and Securities and Exchange Commission.

Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economics Dynamic and Control. 12, 231-254.

Johansen, S., Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration with applications to the demand for money. Oxford Bulletin of Economics and Statistics. 52, 169-210.

Lee, C., Chang, C., 2005. Structural breaks, energy consumption, and economic growth revisited: Evidence from Taiwan. Energy Economics. 27, 857-872.

Lee, J., Strazicich, M., 2001. Break point estimation and spurious rejections with endogenous unit root tests. Oxford bulletin of Economics and Statistics. 63, 535-558.

Oh, W., Lee, K., 2004. Causal relationship between energy consumption and GDP revisited: the case of Korea 1979-1999. Energy Economics. 26, 51-59.

Pesaran, M. H., Yongcheol, S., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics. 16, 289-326.

Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica. 57, 1361-1401.

Perron, P., 1997. Further evidence on breaking trend functions in macroeconomic variables. Journal of Econometrics. 80, 355-385.

Phillips, P.C.B., Perron, P., 1988. Testing for unit root in time series regression. Biometrica. 5, 335-346.

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

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 USA, a multivariate approach. Energy Economics. 15, 137-150.

Toda, H.Y., Phillips, P.C.B., 1993. Vector aurorregressions 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. 225-250.

Weber, C.E., 2001. Alternative lag length selection criteria and the split-trend stationary hypothesis. Applied Economics. 33, 237-247.

Wolde-Rufael, Y., 2006. Electricity consumption and economic growth: a time series experience for 17 African countries. Energy Policy. 34, 1106-1114.

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

Zarraga, A., 1998. Análisis de causalidad entre rendimientos y volumen. Investigaciones económicas. XXII(1), 45-67.

Zivot, E., Andrews, D.W.K., 1992. Further evidence on the great crash, the oil price shock, and the unit root hypothesis. Journal of Business and Economic Statistics. 10, 251-270.

Appendix A

Let U_t and W_t, $t = 1, 2, ...$ denote two strictly stationary and weakly dependent time series. Let

$$\boldsymbol{U}_t^m \equiv (u_t, u_{t+1}, \ldots, u_{t+m-1}), \quad m = 1, 2, \ldots, \quad t = 1, 2, \ldots \tag{7}$$

$$\boldsymbol{U}_{t-Lu}^{Lu} \equiv (u_{t-Lu}, u_{t-Lu+1}, \ldots, u_{t-1}), \;\; Lu = 1, 2, \ldots, \;\; t = Lu + 1, Lu + 2, \ldots \tag{8}$$

$$\boldsymbol{W}_{t-Lw}^{Lw} \equiv (w_{t-Lw}, w_{t-Lw+1}, \ldots, w_{t-1}), Lw = 1, 2, \ldots, \;\; t = Lw + 1, Lw + 2, \ldots, \tag{9}$$

denote the m-length lead vector of U_t and the Lu-length and Lw-length lag vectors of U_t and W_t, respectively.

For given values of m, Lu and $Lw \geq 1$ and for $e > 0$, W does not strictly Granger cause U if:

$$Pr\left(\| \boldsymbol{U}_t^m - \boldsymbol{U}_s^m \| < e \,\middle|\, \| \boldsymbol{U}_{t-Lu}^{Lu} - \boldsymbol{U}_{s-Lu}^{Lu} \| < e, \| \boldsymbol{W}_{t-Lw}^{Lw} - \boldsymbol{W}_{s-Lw}^{Lw} \| < e\right)$$

$$= Pr\left(\| \boldsymbol{U}_t^m - \boldsymbol{U}_s^m \| < e \,\middle|\, \| \boldsymbol{U}_{t-Lu}^{Lu} - \boldsymbol{U}_{s-Lu}^{Lu} \| < e\right), \tag{10}$$

where $Pr(\cdot)$ and $\|\cdot\|$ denote the probability and the maximum norm, respectively. The maximum norm for $\boldsymbol{Z} \equiv (Z_1, Z_2, \ldots, Z_K) \in \mathcal{R}^K$ is defined in Hiemstra and Jones (1994) as $max(Z_i), i = 1, 2, \ldots, K$.

The conditional probability that two arbitrary m-length lead vectors of U_t are within a distance e of each other given that the corresponding Lu-length lag vectors of U_t and Lw-length lag vectors of W_t are within e of each other equals the conditional probability that two arbitrary m-length lead vectors of $\{U_t\}$ are within the distance e of each other, given that their corresponding Lu-length lag vectors are within the same distance. That is, whether or not the condition that the Lw-length lag vectors of W_t are within the distance e is included does not affect the probability.

Hiemstra and Jones (1994) express the above conditional probabilities in terms of the corresponding ratios of joint probabilities, and obtaine the following noncausality condition:

$$\frac{C1(m+Lu, Lw, e)}{C2(Lu, Lw, e)} = \frac{C3(m+Lu, e)}{C4(Lu, e)}, \tag{11}$$

for given values of m, Lu and $Lw \geq 1$ and $e > 0$, where the joint probabilities are defined as:

$$C1(m+Lu, Lw, e) \equiv Pr\left(\| \boldsymbol{U}_{t-Lu}^{m+Lu} - \boldsymbol{U}_{s-Lu}^{m+Lu} \| < e, \| \boldsymbol{W}_{t-Lw}^{Lw} - \boldsymbol{W}_{s-Lw}^{Lw} \| < e\right) \tag{12}$$

$$C2(Lu, Lw, e) \equiv Pr\left(\| \boldsymbol{U}_{t-Lu}^{Lu} - \boldsymbol{U}_{s-Lu}^{Lu} \| < e, \| \boldsymbol{W}_{t-Lw}^{Lw} - \boldsymbol{W}_{s-Lw}^{Lw} \| < e\right) \tag{13}$$

$$C3(m+Lu, e) \equiv Pr\left(\| \boldsymbol{U}_{t-Lu}^{m+Lu} - \boldsymbol{U}_{s-Lu}^{m+Lu} \| < e\right) \tag{14}$$

$$C4(Lu, e) \equiv Pr\left(\| \boldsymbol{U}_{t-Lu}^{Lu} - \boldsymbol{U}_{s-Lu}^{Lu} \| < e\right) \tag{15}$$

Estimators of the joint probabilities in equations (12) to (15) are used to test the condition in equation (11). Let $\{u_t\}$ and $\{w_t\}$ for $t = 1, 2, \ldots, T$, be the time series of realizations on U and W and let $\{\boldsymbol{u}_t^m\}$, $\{\boldsymbol{u}_{t-Lu}^{Lu}\}$ and $\{\boldsymbol{w}_{t-Lw}^{Lw}\}$ denote the m-length lead and and Lu-length lag of $\{u_t\}$ and the Lw-length lag vector of $\{w_t\}$, respectively.

Let $I(\boldsymbol{Z}_1, \boldsymbol{Z}_2, e)$ be a kernel that equals 1 if two conformable vectors $\boldsymbol{Z}_1$ and $\boldsymbol{Z}_2$ are within a distance e of each other and zero otherwise. Taking into account these definitions, the estimators of the joint probabilities in equations (12) to (15) can be expressed as follows:

$$\begin{aligned}\hat{C}1(m+Lu, Lw, e, n) \;\equiv\; & \frac{2}{n(n-1)} \sum_{t<s}\sum I(\boldsymbol{u}_{t-Lu}^{m+Lu}, \boldsymbol{u}_{s-Lu}^{m+Lu}, e) \\ & \cdot I(\boldsymbol{w}_{t-Lw}^{Lw}, \boldsymbol{w}_{s-Lw}^{Lw}, e) \end{aligned} \tag{16}$$

$$\begin{aligned}\hat{C}2(Lu, Lw, e, n) \;\equiv\; & \frac{2}{n(n-1)} \sum_{t<s}\sum I(\boldsymbol{u}_{t-Lu}^{Lu}, \boldsymbol{u}_{s-Lu}^{Lu}, e) \\ & \cdot I(\boldsymbol{w}_{t-Lw}^{Lw}, \boldsymbol{w}_{s-Lw}^{Lw}, e) \end{aligned} \tag{17}$$

$$\hat{C}3(m+Lu, e, n) \;\equiv\; \frac{2}{n(n-1)} \sum_{t<s}\sum I(\boldsymbol{u}_{t-Lu}^{m+Lu}, \boldsymbol{u}_{s-Lu}^{m+Lu}, e) \tag{18}$$

$$\hat{C}4(Lu, e, n) \;\equiv\; \frac{2}{n(n-1)} \sum_{t<s}\sum I(\boldsymbol{u}_{t-Lu}^{Lu}, \boldsymbol{u}_{s-Lu}^{Lu}, e) \tag{19}$$

$t, s = \max(Lu, Lw) + 1, \ldots, T - m + 1, \;\; n = T + 1 - m - \max(Lu, Lw).$

Using these estimators and for given values of m, Lu and $Lw \geq 1$ and $e > 0$, if $\{W_t\}$ does not strictly Granger cause $\{U_t\}$ then:

$$\begin{aligned}\sqrt{n}\left(\frac{\hat{C}1(m+Lu, Lw, e, n)}{\hat{C}2(Lu, Lw, e, n)} - \frac{\hat{C}3(m+Lu, e, n)}{\hat{C}4(Lu, e, n)}\right) & \\ \stackrel{a}{\sim} \mathcal{N}\left(0, \sigma^2(m, Lu, Lw, e)\right), & \end{aligned} \tag{20}$$

where $\sigma^2(m, Lu, Lw, e)$ and a consistent estimator for it can be found in Hiemstra and Jones (1994). As Hiemstra and Jones (1994) point out, the test statistic in equation (20) should be evaluated with right-tailed critical values when testing for Granger causality.

Table 1: Results of the Granger causality test

Null hypothesis	F-statistic	p-value	Decision
LGDP does not cause LEC	2.7992	0.07998	Reject*
LEC does not cause LGDP	0.4850	0.62133	Do not reject

* Indicates the rejection of the null hypothesis for a probability value of 0.10.

Table 2: Results of ADF unit root tests

	Levels	First differences
Variables	ADF	ADF
LEC	-1.55(2)	-5.68(1)*
LGDP	-2.28(5)	-3.42(4)*

The numbers in parenthesis are the optimum number of lags determined using Akaike's information criteria. * Represents the rejection of the null hypothesis at 5% significance level.

Table 3: Results of Pesaran et al. (2001) cointegration tests

Dependent variable	F-statistic
ΔLEC	0.7097
$\Delta LGDP$	1.5577

The results correspond to equations (3) and (4) for $m = 2$. The F-statistic is non-standard and is tabulated in Pesaran et al. (2001). The tests were also applied using different values of m but the results do not change.

Table 4: Results of the Granger causality test for the series in first differences

Null hypothesis	F-statistic	p-value	Decision
LGDP does not cause LEC	3.3437	0.07742	Reject*
LEC does not cause LGDP	0.3389	0.56477	Do not reject

* Indicates the rejection of the null hypothesis for a probability value of 0.10.

Table 5: Results of the nonlinear Granger causality test

Null hypothesis	Statistic	Decision
Case a		
LGDP does not cause LEC	0.03213	Do not reject
LEC does not cause LGDP	-1.27773	Do not reject
Case b		
LGDP does not cause LEC	0.06171	Do not reject
LEC does not cause LGDP	-0.10430	Do not reject

Case a shows the results of the nonlinear causality test applied to the standardized residuals of the estimated VAR(3) for the series in levels. Case b shows the results of the test applied to the standardized residuals of the estimated VAR(1) for the series in first differences.

Figure 1: Log of electricity consumption

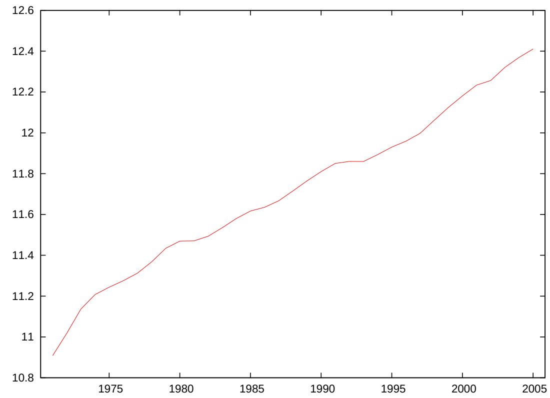

Figure 2: Log of real GDP