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Electricity Consumption and Economic Growth: Evidence from Spain

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Abstract

The paper investigates both 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. On the contrary, we find no evidence of nonlinear Granger causality between the series in either direction.

JEL classification: C32, Q40

Keywords: Electricity consumption; economic growth; causality.

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1 Introduction

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

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 more complex links than the linear ones to study the existence of non-linear dynamic relations.

The energy economics literature has developed 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 an active empirical research during the past two decades. In disaggregated level, electricity consumption is also of special interest. Most of the findings conclude that there is a strong relationship between both variables. Ferguson et al. (2000) find correlation between electricity use and wealth creation in 100 developing countries, furthermore correlation is stronger between electricity use and wealth than there is 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 into four groups. First, a large number of studies find unidirectional causality running from the electricity consumption to the GDP. We remark the studies by Altinay and Karagol (2005) for Turkey who 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, unidirectional causality running from economic growth to electricity consumption. This is the case of Ghosh (2002) for India in 1950-1997, Fatai et al. (2004) for New Zealand and Australia in 1960 to 1999, and Hatemi and Irandoust (2005) for Sweden in 1965-2000. A third group is those studies that find bi-directional causality. This is the case of Soytas and Sari (2003) for Argentina, Oh et al. (2004) for Korea in 1970-1999 and also Yoo (2005) for Korea in 1970-2002. And the last group comprises all the studies that find no causal linkages between energy, or even electricity, consumption and

economic growth, like Cheng (1995) and Stern (1993) for the USA in 1947-1990. Wolde (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, 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 reliable and 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 be in 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 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

2.1 Linear Granger causality

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 by using lagged values of Y .

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:

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

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 being stationary since using non-stationary data can yield spurious causality results (see Sims et al. (1990) or Toda and Phillips (1993)).

If the series are non-stationary they may also be cointegrated, that is, there may be an stationary relationship between the series, although 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. On the contrary, if the series are integrated but not cointegrated, the causality tests may be implemented by estimating a VAR in first differences of the series to achieve stationarity so that the conventional asymptotic theory is valid for hypothesis testing.

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

Some other unit root tests have been developed where 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 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) proposed 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 about which is the best method neither to select the lag length in the regression equation nor to estimate the break point. However, the results are crucial since incorrect decisions will affect inference about the order of integration of the series.

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

Therefore, this testing sequence previous 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 to estimate a VAR for the 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 to estimate 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. Then, linear or nonlinear restrictions on the first p coefficient matrices of the model can be tested using standard Wald tests ignoring the last d_{max} lagged vectors of the variables. Dolado and Lütkepohl (1996) also propose to estimate 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 specially attractive for the case we are not sure whether the series are stationary or integrated of order one. Among others, Altinay and Karagol (2005) or Wolde-Rufael (2006) 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. The method makes it possible to draw a conclusive inference about cointegration without the 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 tradicional Granger causality tests in a VAR model for the series in first differences. Then, we compare the results of causality tests obtained by both methods and check their robustness.

2.2 Non-Linear Granger causality

One problem of the 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 to test for nonlinear causal relations that, by construction, cannot be detected by traditional linear Granger causality tests. This methodology has been used in different fields (Baek and Brock (1992), Jaditz and Jones (1993), Hiemstra and Jones (1994), Hiemstra and Kramer (1997) and Zarraga (1998), among others) finding in some cases a nonlinear Granger causality between the studied series.

In this paper we follow the test Hiemstra and Jones (1994) propose 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 nonlinear predictive power.

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

$$\mathbf{U}_t^m \equiv (u_t, u_{t+1}, \dots, u_{t+m-1}), \quad m = 1, 2, \dots, \quad t = 1, 2, \dots$$

$$\mathbf{U}_{t-Lu}^{Lu} \equiv (u_{t-Lu}, u_{t-Lu+1}, \dots, u_{t-1}), \quad Lu = 1, 2, \dots, \quad t = Lu + 1, Lu + 2, \dots$$

$$\mathbf{W}_{t-Lw}^{Lw} \equiv (w_{t-Lw}, w_{t-Lw+1}, \dots, w_{t-1}), \quad Lw = 1, 2, \dots, \quad t = Lw + 1, Lw + 2, \dots,$$

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:

$$\begin{aligned} Pr \left(\left\| \mathbf{U}_t^m - \mathbf{U}_s^m \right\| < e \mid \left\| \mathbf{U}_{t-Lu}^{Lu} - \mathbf{U}_{s-Lu}^{Lu} \right\| < e, \left\| \mathbf{W}_{t-Lw}^{Lw} - \mathbf{W}_{s-Lw}^{Lw} \right\| < e \right) \\ = Pr \left(\left\| \mathbf{U}_t^m - \mathbf{U}_s^m \right\| < e \mid \left\| \mathbf{U}_{t-Lu}^{Lu} - \mathbf{U}_{s-Lu}^{Lu} \right\| < e \right), \end{aligned}$$

where $Pr(\cdot)$ and $\|\cdot\|$ denote the probability and the maximum norm, respectively¹.

¹The maximum norm for $\mathbf{Z} \equiv (Z_1, Z_2, \dots, Z_K) \in \mathcal{R}^K$ is defined in Hiemstra and Jones (1994) as $\max(Z_i), i = 1, 2, \dots, K$.

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, including or not the condition that the Lw -length lag vectors of W_t are within the distance e does not affect the probability.

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

$$\frac{C1(m + Lu, Lw, e)}{C2(Lu, Lw, e)} = \frac{C3(m + Lu, e)}{C4(Lu, e)}, \quad (2)$$

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

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

$$C2(Lu, Lw, e) \equiv Pr \left(\| \mathbf{U}_{t-Lu}^{Lu} - \mathbf{U}_{s-Lu}^{Lu} \| < e, \| \mathbf{W}_{t-Lw}^{Lw} - \mathbf{W}_{s-Lw}^{Lw} \| < e \right) \quad (3)$$

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

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

Estimators of the joint probabilities in equations (3) are used to test the condition in equation (2). Let $\{u_t\}$ and $\{w_t\}$ for $t = 1, 2, \dots, T$, be the time series of realizations on U and W and let $\{\mathbf{u}_t^m\}$, $\{\mathbf{u}_{t-Lu}^{Lu}\}$ and $\{\mathbf{w}_{t-Lw}^{Lw}\}$ denote the m -length lead and and Lu -length lag of $\{u_t\}$ and the Lw -length lag vector of $\{w_t\}$, respectively.

Let $I(\mathbf{Z}_1, \mathbf{Z}_2, e)$ be a kernel that equals 1 if two conformable vectors \mathbf{Z}_1 and \mathbf{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 (3) can be expressed as follows:

$$\hat{C}1(m + Lu, Lw, e, n) \equiv \frac{2}{n(n-1)} \sum_{t < s} \sum I(\mathbf{u}_{t-Lu}^{m+Lu}, \mathbf{u}_{s-Lu}^{m+Lu}, e) \cdot I(\mathbf{w}_{t-Lw}^{Lw}, \mathbf{w}_{s-Lw}^{Lw}, e)$$

$$\begin{aligned}
\hat{C}2(Lu, Lw, e, n) &\equiv \frac{2}{n(n-1)} \sum_{t < s} \sum I(\mathbf{u}_{t-Lu}^{Lu}, \mathbf{u}_{s-Lu}^{Lu}, e) \\
&\quad \cdot I(\mathbf{w}_{t-Lw}^{Lw}, \mathbf{w}_{s-Lw}^{Lw}, e) \\
\hat{C}3(m+Lu, e, n) &\equiv \frac{2}{n(n-1)} \sum_{t < s} \sum I(\mathbf{u}_{t-Lu}^{m+Lu}, \mathbf{u}_{s-Lu}^{m+Lu}, e) \\
\hat{C}4(Lu, e, n) &\equiv \frac{2}{n(n-1)} \sum_{t < s} \sum I(\mathbf{u}_{t-Lu}^{Lu}, \mathbf{u}_{s-Lu}^{Lu}, e)
\end{aligned}$$

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

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:

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

where $\sigma^2(m, Lu, Lw, e)$ and a consistent estimator for it can be found in Hiemstra and Jones (1994)².

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 it publishes monthly bulletins with the levels of consumption for the entire system including islands and outer territories. The real GDP is measured in constant prices of 1986 and denominated in millions of euros, are extracted from *Instituto Nacional de Estadística, INE*, which coordinates all the 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.

²As Hiemstra and Jones (1994) point out, the test statistic in equation (4) should be evaluated with right-tailed critical values when testing for Granger causality.

Figure 1: Log of electricity consumption

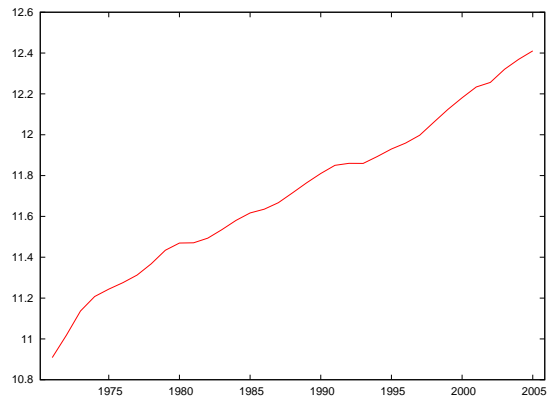
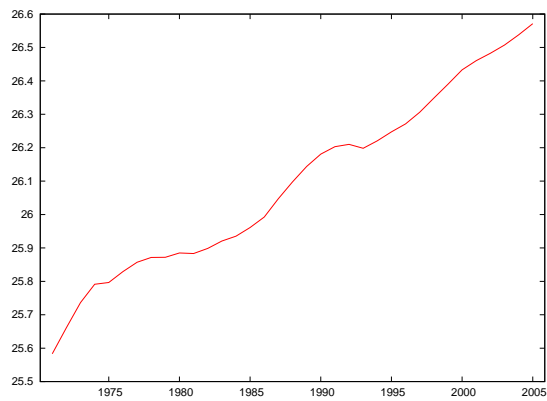


Figure 2: Log of real GDP



As can be seen there is an increasing trend in both variables. The real GDP exhibits two periods of negative growth corresponding to 1973 and 1993, whereas electricity consumption maintains an increasing path that only in 1993 is null.

3.2 Dolado and Lütkepohl 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 criterion. The optimum selected lag is 2, thus, we estimate the following VAR model by OLS setting $p = 3$ lags, that is, the optimum number of lags plus one.

$$\begin{bmatrix} LEC_t \\ LGDP_t \end{bmatrix} = \begin{bmatrix} \nu_1 \\ \nu_2 \end{bmatrix} + \begin{bmatrix} a_{11,1} & a_{12,1} \\ a_{21,1} & a_{22,1} \end{bmatrix} \begin{bmatrix} LEC_{t-1} \\ LGDP_{t-1} \end{bmatrix} + \begin{bmatrix} a_{11,2} & a_{12,2} \\ a_{21,2} & a_{22,2} \end{bmatrix} \begin{bmatrix} LEC_{t-2} \\ LGDP_{t-2} \end{bmatrix} + \begin{bmatrix} a_{11,3} & a_{12,3} \\ a_{21,3} & a_{22,3} \end{bmatrix} \begin{bmatrix} LEC_{t-3} \\ LGDP_{t-3} \end{bmatrix} + \begin{bmatrix} U_t \\ W_t \end{bmatrix} \quad (5)$$

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: 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.

As can be seen, for a probability value of 0.10 there is evidence of a uni-directional Granger causality running from Spanish real GDP to electricity consumption, whereas there is no evidence of Granger causality running in the other 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 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 tests³. As

³For simplicity, we only present the ADF test results. The results of the PP unit root test are similar and are available upon request.

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: Results of ADF unit root tests

Variables	Levels	First differences
	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.

As we find evidence that both series are integrated of order one⁴, 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:

$$\Delta LEC_t = \alpha_1 + \sum_{i=1}^m \beta_{1i} \Delta LEC_{t-i} + \sum_{i=1}^m \delta_{1i} \Delta LGDP_{t-i} + \eta_{11} LEC_{t-1} + \eta_{12} LGDP_{t-1} + u_{1t} \quad (6)$$

$$\Delta LGDP_t = \alpha_2 + \sum_{i=1}^m \beta_{2i} \Delta LEC_{t-i} + \sum_{i=1}^m \delta_{2i} \Delta LGDP_{t-i} + \eta_{21} LEC_{t-1} + \eta_{22} LGDP_{t-1} + u_{2t} \quad (7)$$

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 (6) and $H_0 : \eta_{21} = \eta_{22} = 0$ in equation (7). Table 3 presents the results of Pesaran et al. (2001) test for cointegration. Under the null of no cointegration, the asymptotic distribution of the statistic is non-standard. Pesaran et al. (2001) provides 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

⁴We 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.

falls outside the critical bounds, a conclusive inference can be drawn without needing to know the order of integration of the series. For the case of Spanish GDP and electricity consumption the computed F -statistics are below the lower critical value, therefore the null hypothesis of no cointegration between the data series cannot be rejected⁵.

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 (6) and (7) for $m = 2$. The F -statistic is non-standard and is tabulated in Pesaran et al. (2001). The tests have been also applied using different values of m but the results do not change.

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 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 series⁶:

$$\Delta LEC_t = \nu_1 + \gamma_{11}\Delta LEC_{t-1} + \gamma_{12}\Delta LGDP_{t-1} + U_t \quad (8)$$

$$\Delta LGDP_t = \nu_2 + \gamma_{21}\Delta LEC_{t-1} + \gamma_{22}\Delta LGDP_{t-1} + W_t \quad (9)$$

and test the null hypothesis $H_0 : \gamma_{12} = 0$ that LEC does not cause LGDP in Granger sense and $H_0 : \gamma_{21} = 0$ that LGDP does not cause LEC in Granger sense 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 exists a unidirectional causality running from Spanish real GDP to electricity consumption.

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). It shows the robustness of the results to different methodologies. Also, Altinay and Karagol (2005) prove

⁵The Johansen greatest eigenvalue and trace tests for cointegration has also been applied, but the results do not change.

⁶The lag length is chosen by using the Akaike's information criterion for a maximum of up to 4 lags.

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.

the robustness of the 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 a 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 $e = 0.5^7$. We calculate the standardized statistic (4) 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 any direction. The results applying the test 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 the robustness of the results, as it was the case for the tests of linear causality.

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.

⁷We also use a scale parameter value of 1.5 but these results are not reported since they are similar to the results reported for $e = 0.5$. The complete set of results is available from the authors upon request.

Table 5: Results of the nonlinear Granger causality test

Null hypothesis	Statistic	Decision
<i>Case a</i>		
LGDP does not cause LEC	0.03213	Do not reject
LEC does not cause LGDP	-1.27773	Do not reject
<i>Case b</i>		
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.

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 test 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 tests. Namely, there is a unidirectional causality running from GDP to electricity consumption.

The result is in the same line as the studies for some countries in the European Union as Sweden, and countries as far as Australia and New Zealand (Fatai et al. (2004)).

These results indicate that past values of electricity consumption improve forecasts of movements in economic growth, but they do it in a linear manner and therefore the causal relation between the series is not very abrupt or complex to be nonlinear. The two variables are not indeed directly related because most likely both variables are determined by factors that are not considered in this study. What we can certainly assert is that electricity consumption can be used as an indicator of economic growth.

The other important conclusion is that we do not find evidence of nonlinear causality between electricity consumption and economic growth. This result may arise because we use yearly observations. Thus, it is very difficult to obtain more complex relationship between both variables.

Finally, we want to emphasize the importance of this type of studies not only by the amount of literature that has been published, but also how policy makers have used them. In particular, the US Department of Energy requested a report in 1988 on the relation between economic growth and electricity to design development programs and proper incentives for the

private sector. We believe this is also necessary in Spain to attend to of the challenges in the near future: Kyoto protocol of CO₂ emissions, the use of more efficient technologies of generation that do not hinder the target of sustained economic growth.

5 References

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