Viewpoint

Linear and nonlinear causality between sectoral electricity consumption and economic growth: Evidence from Taiwan

Yang Cheng-Lang [a], Hung-Pin Lin [b,*], Chih-Heng Chang [a]

[a] Department of Managerial Economics, Nanhua University, Chiayi 62102, Taiwan
[b] Department of International Business and Trade, Shu-Te University, Kaohsiung 82445, Taiwan

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ABSTRACT

This study investigates the linear and nonlinear causality between the total electricity consumption (TEC) and real gross domestic production (RGDP). Unlike previous literature, we solve the undetermined relation between RGDP and electricity consumption by classifying TEC into industrial sector consumption (ISC) and residential sector consumption (RSC) as well as investigating how TEC, ISC, and RSC influence Taiwan's RGDP. By using the Granger's linear causality test, it is shown that (i) there is a bidirectional causality among TEC, ISC, and RGDP, but a neutrality between RSC and RGDP with regard to the linear causality and (ii) there is still a bidirectional causality between TEC and RGDP, but a unidirectional causality between RSC and RGDP with regard to the nonlinear causality. On the basis of (i) and (ii), we suggest that the electricity policy formulators loosen the restriction on ISC and limit RSC in order to achieve the goal of economic growth.

1. Introduction

In the 19th century, Michael Faraday's discovery of electromagnetic induction contributed to the advancement of human civilization and ushered in a new age of electrification. Indeed, this historic invention has not only upgraded the living standards of human beings but also increased product efficiency and economic growth. However, the 20th century brought with it the effect of global warming and environmental consciousness; these developments led to the reconsideration of environmental protection rules. To address this issue, delegates from more than 160 countries met in Kyoto, Japan, in 1997 to draft an agreement called the Kyoto Protocol. This agreement demands a decrease in carbon dioxide emissions. The U.S. tends to not sign any protocol that fails to include binding targets and timetables for both developing and industrialized nations or a protocol that would seriously harm its economy. This leads to a dilemma regarding whether the policy focus should be on energy saving and carbon reduction or economic growth.

Many studies have discussed the relation between electricity consumption and real gross domestic production (RGDP) by using a causality test. However, the effect of this relation has hitherto not been discussed. Existing studies on this topic can be classified into four types. The first type, which includes Ho and Siu (2007), Shiu and Lam (2004), and Narayan and Singh (2007), indicates that electricity consumption affects RGDP. On the contrary, the second type, comprising Ghosh (2002), Jumbe (2004), and Narayan and Smyth (2005), suggests that RGDP affects electricity consumption. The third type, which includes Yang (2000), Yoo (2005), and Oh and Lee (2004), suggests that there is a bidirectional causality between RGDP and electricity consumption. Yemane (2006) and Yoo (2006), which belong to the fourth type, indicate that a neutrality exists between RGDP and electricity consumption. In order to formulate the most feasible electric policy that maximizes social welfare and lowers the resulting impact on the economic system, it is essential for policy makers to determine whether electricity consumption benefits RGDP or RGDP drives the increase in electricity consumption.

To clarify this undetermined relation between RGDP and electricity consumption, we classify total electricity consumption (TEC) into industrial sector consumption (ISC) and residential sector consumption (RSC) for the following reasons. First, we consider the factor of TEC of different parts of electricity consumption sectors. Therefore, each sector is assigned different weights of TEC summation, varying with time. For example, in the early period of Taiwan's agricultural society, agricultural electricity consumption accounted for a higher percentage of TEC. However, with the subsequent industrialization of Taiwan, industrial electricity consumption mainly accounted for a higher percentage of TEC. Hence, the classification of TEC not only helps us to analyze the causality but also distinguishes the essential types of electricity consumption. Second, on the basis of economic intuition, higher ISC may reflect increased investments on machinery equipment, resulting in higher economic growth.

* Corresponding author. Tel.: +886 922984204.
E-mail address: lhp0606@stu.edu.tw (H.-P. Lin).

Similarly, higher RGDP accumulation may increase a firm's capital investment capacity and help increase ISC. This shows that there may be a bidirectional causality between ISC and RGDP. Third, with regard to RSC, the increase in RGDP increases the purchasing power of the public. Therefore, the public can afford an increasing number of luxury electronic devices and appliances; this leads to an increase in RSC, which reveals a unidirectional causality relation between RGDP and RSC. In light of these three reasons, we can conclude that as long as each sector can be distinguished and the causality relation between RGDP and each sector is clear, electric policy formulators will have sufficient information to devise specific rules or policies to control the quantity of consumption.

In this study, we attempt to investigate how TEC, ISC, and RSC influence Taiwan's RGDP by using two empirical tools: Granger's (1969) linear causality test and the nonlinear causality test proposed by Hiemstra and Jones (1994). The reason for using nonlinear causality test is as Chiou-Wei et al. (2008) and Lee and Chang (2005) suggested that economic incidents, changes in the environment, electricity policy alterations, and fluctuations in oil prices can lead to structural changes in the pattern of electricity consumption for a given time period under study. This creates a scope for a nonlinear relationship between electricity consumption and economic growth. Because of the possibility of a nonlinear relation among variables, we use the i.i.d. test proposed by Brock et al. (1987) to determine whether the residual in the linear model is nonlinear or not. If the residual is rejected in the i.i.d. test, the nonlinear causality test suggested by Hiemstra and Jones (1994) can be executed. The empirical results of the linear causality test show a bidirectional causality among TEC, ISC, and RGDP but not between RSC and RGDP. On the contrary, after testing the residual in the linear model, we find that a nonlinear relationship exists among TEC, RSC, and RGDP. In addition, the nonlinear causality test results indicate that a bidirectional causality still exists between TEC and RGDP, but there is a unidirectional causality between RSC and RGDP.

The rest of this paper is organized as follows. Section 2 constructs the empirical methods, including the Granger linear causality, BDS, and nonlinear causality tests. Section 3 explains the empirical results. Finally, concluding remarks and policy implications are presented in Section 4.

2. Empirical model

2.1. Linear causality test

The bivariate Granger causality tests help in examining the relationship between two variables. The two variables X and Y evaluate whether the past values of X are useful to predict Y, and Y is said to be Granger-caused by X if X helps to predict Y, and vice versa. On the basis of Granger's causality test, we use the vector autoregression (VAR) model proposed by Sims (1980) to conduct the causality tests. Consider a bivariate VAR model

$$\Delta Y_t = a_1 + \sum_{i=1}^{m} b_{1i}\Delta X_{t-i} + \sum_{j=1}^{m} g_{1j}\Delta Y_{t-j} + v_{1t} \tag{1}$$

$$\Delta X_t = a_2 + \sum_{i=1}^{m} b_{2i}\Delta X_{t-i} + \sum_{j=1}^{m} g_{2i}\Delta Y_{t-j} + v_{2t} \tag{2}$$

where a_1 and a_2 are intercept terms; b and g represent the estimate coefficients; and m is the lag order of the model, which is selected by the Akaike information criterion (AIC). The null

hypothesis supposes that X does not Granger-cause Y in Eq. (1) and Y does not Granger-cause X in Eq. (2), which could be represented as $b_{1i}=0$ and $g_{2i}=0$ $(i=1,2,\ldots,m)$, respectively. In addition, we apply Wald statistics, as suggested by the Granger (1969) approach, to examine the joint hypothesis of $b_{1i}=0$ and $g_{2i}=0$. Furthermore, since the Granger (1969) approach requires the variables in the system to be stationary, it is important to determine whether or not the variables have a unit root. We apply the augmented Dickey–Fuller (ADF) test in our study and select the lag order by the AIC.

2.2. The Hiemstra–Jones test

As stated by Baek and Brock (1992) and Hiemstra and Jones (1994), taking the linear approach (for example, using the Granger test) leads to a problem, namely, a low power in detecting a nonlinear causal relation. Hiemstra and Jones (1994) modified a version of the Baek and Brock (1992) test, which differed from Granger's (1969) linear causality test; they then proposed a nonlinear Granger's causality test based on nonparametric estimators of temporal relations within and across time series. Let $F(X_t|I_{t-1})$ denote the conditional probability distribution of X_t, given the information set I_{t-1}, which comprises an L_x-length lagged vector of X_t and an L_y-length lagged vector of Y_t. If the vector of past Y-values is removed from the information set and the distribution of current X-values is not affected, Y is said to not Granger-cause X. Therefore, the null hypothesis of Hiemstra and Jones is expressed as follows:

$$H_0 : F(X_t|I_{t-1}) = F(X_t|I_{t-1} - Y_{t-L_y}^{L_y}) \tag{3}$$

where $Y_{t-L_y}^{L_y}$ represents the $t-L_y$—length lagged vector of Y. $Y_{t-L_y}^{L_y} = (Y_{t-L_y}, Y_{t-L_y+1}, \ldots, Y_{t-1})$.

The null hypothesis given in Eq. (3) implies that for all $\varepsilon > 0$

$$P(\|X_t^m - X_s^m\| < \varepsilon | \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < \varepsilon, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < \varepsilon)$$
$$= P(\|X_t^m - X_s^m\| < \varepsilon | \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < \varepsilon) \tag{4}$$

where $P(A|B)$ denotes the conditional probability of A given B, and $\|\cdot\|$ represents the supremum norm. Eq. (4) states that in addition to the lagged L_y-length lagged vector of Y_t being ε−closed, the conditional probability that two arbitrary m-length lead vectors of X_t are within distance ε, given that the lagged L_x-length lagged vector of X_t is ε−closed, will be the same. Moreover, Hiemstra and Jones show that U-statistics follow normal distribution under Eq. (3):

$$U_{statistics} = \sqrt{n}\left[\frac{C_1(m+L_x, L_y, \varepsilon)}{C_2(L_x, L_y, \varepsilon)} - \frac{C_3(m+L_x, \varepsilon)}{C_4(L_x, \varepsilon)}\right] \sim N(0, \sigma^2(m, L_x, L_y, \varepsilon)) \tag{5}$$

where $C_1(m+L_x, L_y, \varepsilon) = P(\|X_{t-L_x}^{m+L_x} - X_{s-L_x}^{m+L_x}\| < \varepsilon, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < \varepsilon)$, $C_2(L_x, L_y, \varepsilon) = P(\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < \varepsilon, \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < \varepsilon)$, $C_3(m+L_x, \varepsilon) = P(\|X_{t-L_x}^{m+L_x} - X_{s-L_x}^{m+L_x}\| < \varepsilon)$, $C_4(L_x, \varepsilon) = P(\|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < \varepsilon)$.

3. Empirical analysis

3.1. Data source

The empirical data source is Taiwan's quarterly data from 1982 to 2008 on the following four important variables: TEC, RGDP, ISC, and RSC. The RGDP data are sourced from the Directorate General of Budget, Accounting and Statistics, Executive Yuan, Taiwan, and the rest, from the Education Statistical Databank, Taiwan.

Evidently, the data for these four variables are seasonally affected; therefore, in order to retard the seasonal factors, we use