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The Electricity Consumption and Economic Growth Nexus in China: A Bootstrap Seemingly Unrelated Regression Estimator Approach

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Abstract Electricity consumption in China has attracted increasing attention by the government in monitoring the economy. The purpose of the study is test whether electricity consumption is an appropriate indicator. To do that, this paper proposes an alternative bootstrap Granger causality test, which can capture the contemporaneous correlation of the term error in the Vector Autoregressive Model, based on a seemingly unrelated regression estimator. Using a quarterly data set containing more dynamic changes, this study reinvestigates the relationship between electricity consumption and economic growth. The results show that there exists a long-run relationship between the two variables. Electricity consumption can be treated as an indicator of the functioning of the economy. A strong unidirectional Granger causality is found running from gross domestic product to electricity consumption. However, the causality relationship from electricity consumption to gross domestic product is relatively weak. Thus, electricity consumption is a useful indicator to check the reliability of GDP data, however, caution is required when using electricity consumption to predict future economic activities in China.

Keywords Electricity consumption · Economic growth · Bootstrap method · Seemingly unrelated regression estimator

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1 Introduction

Experiencing consecutive decline of 6 years, China's economic growth rate dropped to 6.7% in 2016, the lowest one after 1990. China is trying to adjust the industrial structure and reform state-owned enterprises to stop such declining trend. A problem faced by Chinese policymaker is how to monitor the economic activities well using statistics data. The reliability of China's economic data is still in debate. Although the National Bureau of Statistics insists that the data published by them is true and credible, the problem is not occurring in central but local level. China's local government officials have the incentive to exaggerate the economic data for promotion. In January 2017, People's Daily of China reported city and county governments in the northwestern region committed fiscal data fraud from 2011 to 2014. The data fraud will obviously mislead the central government's judgment of economic status.

China is a significant producer and consumer of electricity. It is widely believed that there is a close relationship between electricity consumption and the economic situation in a country. In China's 2014 government work report, Premier Li first adopted electricity consumption as an economic activity indicator. Before this, China's officials at all levels had preferred to use GDP, investment, consumption, fiscal revenue, among others, to gauge economic activity. It is generally believed, compared with these economic indicators, electricity consumption is easier to verify and has less space for data manipulation. However, there are also some debates about veracity of China's electricity data. A report from New York Times in June 2012 said China's local government officials are capable of forcing power plant to inflate their output figures. Subsequently, First Financial Daily of China refuted this point and argued the central government was fully aware of the local real electricity situation because the power industry is basically controlled by few of central enterprises. Local government cannot prevent them to report power generation situation to the central government. So far, the debates about usability of electricity indicator are constrained in news media, no formally academic discussion has been involved yet.

The main question of concern here is whether electricity consumption can be treated as an alternative indicator for monitoring economic activity. Furthermore, whether it can be used to predict economic trends in China is also the main concern. This is both a realistic issue and an academic issue. Many energy economists are interested in the link between electricity and growth. Taken together, they propose four relevant hypotheses (Ozturk 2010; Payne 2010a, b): (1) the growth hypothesis, which assumes that electricity consumption can fuel economic growth; (2) the conversation hypothesis, which assumes that economic growth will foster electricity consumption, not the other way around; (3) the feedback hypothesis, which predicts an interdependent relationship between electricity consumption and economic growth; and (4) the neutrality hypothesis, which assumes there is no link between the two. In addition to these theories, many studies have empirically examined the link between electricity and growth since the work of Kraft and Kraft (1978). The present study contributes to this body of literature by performing a Granger causality test on the two variables in a Vector Autoregressive Model (VAR) system.

Departing from previous literature in this field, the contributions of present paper are as follows. The first contribution is methodological in that this paper proposes a new bootstrap Granger causality test method, which can capture the contemporaneous correlation of the term error in the Vector Autoregressive Model. Although there have been many causality methods based on the bootstrap technique, most ignore such contemporaneous correlation of the term error, which will cause a loss of efficiency in the estimation (Mantalos 2000; Hatemi-J 2002; Hafner and Herwartz 2009; Song and Wang 2016). Second, quarterly data containing more dynamic changes are employed to study China's electricity consumption and economic growth. A major shortcoming of previous works is that they use yearly data to detect the relationship between the two (Shiu and Lam 2004; Yuan et al. 2007). Intuitively, it is illogical to use the previous year's (or older) electricity consumption to predict GDP. In practice, government policymakers and businesses prefer to use quarterly data rather than yearly data for predictions. In the economic reports of other countries, quarterly electricity consumption is usually regarded as a barometer for the economy.

The rest of this paper is organized as follows: Sect. 2 is the literature review existing on the subject; Sect. 3 describes the methodologies; Sect. 4 presents the data and empirical analysis; Sect. 5 is the conclusion.

2 Literature Review

Numerous studies have focused on the relationship between electricity consumption and GDP in countries other than China, examining both equilibrium and causality. These have yielded mixed results, both in terms of the existence of equilibrium and the direction of causality, which may be attributed to method selection, variable selection, or country selection. In existing studies, detecting equilibrium or a cointegration relationship is the first step, and is closely associated with the method adopted in subsequent steps. Based on the Engle–Granger test procedure (Engle and Granger 1987), Yang (2000) examines the relationship between Taiwan Province's GDP and electricity consumption, showing that the two variables are not cointegrated. Similar studies include those of Aqeel and Butt (2001) and Thoma (2004), who used the same approach to examine data on Pakistan and the United States, respectively, and also found no evidence of cointegration. However, most studies do find a cointegration relationship by adopting the Johansen–Juselius cointegration procedure (Johansen 1988; Johansen and Juselius 1990) with the exception of Ghosh (2002) and Yoo and Kim (2006). For example, Fatai et al. (2004) examined data on New Zealand using the above approach, and were not able to reject the null hypothesis of no cointegration. Akinlo (2009) investigated the data on Nigeria and showed that GDP and electricity consumption are cointegrated. The empirical results of Odhiambo (2009) indicate a long-term equilibrium relationship exists between electricity consumption, employment, and economic growth in South Africa. Gurgul and Lach (2012) examined electricity consumption and GDP in Poland, and provided evidence of cointegration between them. However, using the same test method, Ghosh (2002) and Yoo and Kim (2006) argue that no such cointegration relationship exists, based on data on India and Indonesia, respectively. Several studies use other cointegration test procedures. Employing the autoregressive distributed lag (ARDL) bounds testing proposed by Pesaran et al. (2001), Shahbaz et al. (2014) explored the relationship between economic growth, electricity consumption, urbanization, and environmental degradation in the United Arab Emirates. Their results show that a long-run relationship between the variables exists. Using panel data cointegration analyses has recently become popular. Al-mulali et al. (2014), Karanfil and Li (2015), and Osman et al. (2016) found that electricity consumption and economic growth variables are cointegrated based on panel data of Latin American countries, 160 countries, and Gulf Corporation Council countries, respectively.

Conditional on the cointegration test results of the variables, the second stage involves selecting an appropriate Granger causality. If no cointegration exists, the Granger causality test in the VAR is permissible only if the causal variables are made to appear in first differences. Otherwise, the vector error correction model (VECM) or Toda–Yamamoto method should be adopted in order to utilize cointegration information. Using a VAR model in differences, Aqeel and Butt (2001), Ghosh (2002), Thoma (2004), and Yoo and Kim (2006) provide evidence that economic growth can Granger cause electricity consumption, but not vice versa. Based on both the VECM and Toda–Yamamoto methods, Fatai et al. (2004) also finds a unidirectional link from real GDP to electricity consumption. However, using data on Poland, Gurgul and Lach (2012) find a bidirectional Granger causality after employing the VECM and Toda–Yamamoto methods. Using the VECM method, Akinlo (2009) and Odhiambo (2009) find Granger causality from electricity consumption to GDP for two African countries. However, Shahbaz et al. (2014) uses the VECM to show a bidirectional causality relationship for the United Arab Emirates. For Latin American countries, Al-mulali et al. (2014) finds bidirectional causality relationship is only valid for renewable electricity consumption and economic growth.

Fewer studies focus on this relationship in the context of China. Shiu and Lam (2004) studied annual data of electricity consumption and real GDP for a 30-year period, from 1971 to 2000. Their results provided support for the claim that there exists a cointegration relationship between the two variables. They also found unidirectional Granger causality running from electricity consumption to GDP, but that the reverse Granger causality did not exist. A similar study based in China, by Yuan et al. (2007), showed nearly identical results based on annual data for the period 1978–2004. However, the shortcoming of using yearly data means that, although the results of the aforementioned studies are uniformly conclusive, they are less useful for policymakers trying to predict the near future. This study reinvestigates this issue using quarterly data in a VAR system, which is more convenient to use for forecasting than is the VECM.

In addition to the empirical studies on electricity consumption and economic growth, the paper reviews the methodology related to this research. In Granger causality literature, stationarity has attracted increasing concern. If the variables are not stationary, the standard Wald test is unreliable when testing the restrictions of coefficients because of the non-standard asymptotic distribution of the statistic (Park and Phillips 1989; Hacker and Hatemi-J 2006; Toda and Phillips 1993). Therefore, the general Granger causality test procedure may be misleading, if not totally incorrect. There are two strands of solutions to address this issue. The first strand modifies the test statistic, but not the distribution. Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) suggest a simple method, called the modified Granger causality test, to obtain a Wald statistic, following the standard asymptotic distribution by adding VAR lags. That is, if the lag selection procedures find that VAR with p lags is appropriate, VAR($p + d_{\max}$) need to be estimated, where $d_{\max}$ is the maximal order of the suspected integration. Then, the Wald test based on first p coefficient, which has a standard asymptotic distribution, can be performed to detect a Granger causality relationship. The modified Granger causality test can be applied to various levels of variables, regardless of whether they are stationary. Therefore, it is not necessary to pre-test for integration and cointegration, as long as the maximal order of the integration of the process is below the lag number of the VAR system. However, using Monte Carlo experiments, Shukur and Mantalos (2000) found that a modified form of the Granger-causality test performs badly, especially in the case of small samples.

The second strand modifies the distribution, but not the statistic. It continues to use the standard Wald statistic, but replaces the non-standard distribution with an empirical bootstrap distribution obtained using a bootstrap simulation. This method is also known as the bootstrap Granger causality test, and it has been proven that it can correct the size distortion of the Wald test. As a result, there is a growing body of literature on varieties of bootstrap techniques (Mantalos and Shukur 1998; Mantalos 2000; Hacker and Hatemi-J 2006). The present study closely resembles this second strand, and introduces an alternative bootstrap Granger causality test. The novelty of this work is that the residual sampling and the construction of the bootstrap samples are based on a seemingly unrelated regressions (SUR) estimator. In contrast, prior studies have adopted the OLS estimator (Mantalos 2000; Hatemi-J 2002; Hafner and Herwartz 2009; Song and Wang 2016), which is consistent, but not efficient. Using the OLS estimator means they assume that the error terms across equations are contemporaneously uncorrelated. However, because of unobservable influences on the overall system of equations, this is not a realistic assumption. Zellner (1962) proposed the SUR estimator in his seminal work, which uses the correlation among error terms to obtain a more efficient estimator.

3 Methodology

3.1 Granger Causality Test

First, a simple explanation of Granger causality is worth mentioning. A variable is said to Granger cause another variable if the former facilitates the prediction of the latter, or if using past values of the former can decrease the prediction error of the latter. Generally, the Granger test is performed in a VAR(p) system, defined as follows:

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \cdots + \Phi_p Y_{t-p} + \varepsilon_t \tag{1}$$

Since the goal is to examine the causal relationship between electricity consumption and GDP, a bivariate VAR system is employed. Here, Y_t is a 2×1 vector of two components Y_1 and Y_2, p is the lag order of this process, and ε_t is a 2×1 vector of error terms, with the following covariance matrix:

$$V = \begin{bmatrix} \sigma_{11}, & \sigma_{12} \\ \sigma_{12}, & \sigma_{22} \end{bmatrix} \tag{2}$$

Then, (1) can be rewritten as follows:

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} \Phi_{0,1} \\ \Phi_{0,2} \end{bmatrix} + \begin{bmatrix} \Phi_{1,11} & \Phi_{1,12} \\ \Phi_{1,21} & \Phi_{1,22} \end{bmatrix} \times \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \Phi_{p,11} & \Phi_{p,12} \\ \Phi_{p,21} & \Phi_{p,22} \end{bmatrix} \times \begin{bmatrix} Y_{1,t-p} \\ Y_{2,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{3}$$

In this specification, Y_2 does not granger cause Y_1 if the following null hypothesis is true:

$$H_0 : \Phi_{i,12} = 0 \quad \text{for } i = 1, \ldots, p. \tag{4}$$

The standard Wald test statistic is $W = (Rb-r)'[R\mathrm{V}(b)R']^{-1}(Rb-r)$, where the null hypothesis is that $Rb - r = 0$, b is the parameter being studied, and R and r are the constant matrix and vector, respectively. Thus, for exclusion restriction hypothesis (4), the Wald test statistic simplifies to:

$$W = \hat{\Phi}'_{12}[\hat{\mathrm{V}}(\hat{\Phi}_{12})]^{-1}\hat{\Phi}_{12} \tag{5}$$

When the variables contained in the VAR are stationary, W is asymptotically distributed as $\chi^2(p)$ under H_0, which can be adopted to calculate the significance level of the hypothesis test. When the VAR contains $I(1)$ variables, an alternative method is the modified Granger causality test, or Toda–Yamamoto method, which estimates the following VAR system:

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \end{bmatrix} = \begin{bmatrix} \Phi_{0,1} \\ \Phi_{0,2} \end{bmatrix} + \begin{bmatrix} \Phi_{1,11} & \Phi_{1,12} \\ \Phi_{1,21} & \Phi_{1,22} \end{bmatrix} \times \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \Phi_{p+1,11} & \Phi_{p+1,12} \\ \Phi_{p+1,21} & \Phi_{p+1,22} \end{bmatrix} \times \begin{bmatrix} Y_{1,t-1-p} \\ Y_{2,t-1-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{6}$$

In calculating the statistic to detect whether Y_2 Granger causes Y_1 using the modified Granger causality test, the extra parameter of Y_2 should be ignored. Therefore, the null hypothesis remains as shown in (4), even though the lag order of the VAR system is augmented. In this case, the Wald test statistic calculated using (5) has the usual asymptotic $\chi^2(p)$ distribution for the inference.

3.2 SUR Estimators in VAR Systems

Before introducing the bootstrap method, using the SUR estimator in VAR systems (1) should be considered. In order to derive a SUR estimator of VAR(p), a sample set including T periods is considered. Then, model (1) or (3) is rewritten in stacking form:

$$Y = Z\Phi + \varepsilon \tag{7}$$

where Y is a $2T \times 1$ vector, Z is a $2T \times 2(p+1)$ matrix, Φ is a $2(p+1) \times 1$ vector, and ε is $2T \times 1$ vector. At period $t > p$, Z_t is expressed as follows:

$$Z_t = \begin{bmatrix} 1, Y_{1,t-1}, Y_{2,t-1} \cdots Y_{1,t-p}, Y_{2,t-p} & \cdots 0 \cdots \\ \cdots \ 0 \ \cdots & 1, Y_{1,t-1}, Y_{2,t-1} \cdots Y_{1,t-p}, Y_{2,t-p} \end{bmatrix} \tag{8}$$

and Φ has the following form:

$$\Phi = \begin{bmatrix} \Phi_1 \\ \Phi_2 \end{bmatrix}, \quad \text{where } \Phi_i = \begin{bmatrix} \Phi_{0,i} \\ \Phi_{1,i1} \\ \Phi_{1,i2} \\ \vdots \\ \Phi_{p,i1} \\ \Phi_{p,i2} \end{bmatrix} i = 1, 2$$

The covariance of ε has the following form:

$$V(\varepsilon) = \Sigma = \begin{bmatrix} \sigma_{11} I_T, \sigma_{12} I_T \\ \sigma_{12} I_T, \sigma_{22} I_T \end{bmatrix} = V \otimes I_T \tag{9}$$

Based on the above symbol, the generalized least squares (GLS) estimator of Φ is given by:

$$\Phi_{GLS} = (Z'\Sigma^{-1}Z)^{-1} Z'\Sigma^{-1} Y \tag{10}$$

$$V(\Phi_{GLS}) = (Z'\Sigma^{-1}Z)^{-1} \tag{11}$$

In contrast, the ordinary least squares (OLS) estimator of Φ is provided by:

$$\Phi_{OLS} = (Z'Z)^{-1} Z'Y \tag{12}$$

$$V(\Phi_{OLD}) = (Z'Z)^{-1} \tag{13}$$

Although the OLS estimator is used frequently in the existing literature, it does not use information on the covariance in the VAR system. In general, the GLS estimator Φ_{GLS} has a smaller variance and is more efficient than is the OLS estimator, according to Zellner (1962). The GLS estimator in the SUR model is often called the SUR estimator.

Unfortunately, sometimes there is no efficiency gain from using an SUR estimation, even if a correlation between the error terms exists. Kruskal (1968) provided special cases where the efficiency gain disappears, including the situation in which each equation has the same regressors, as in VAR system (1). Now, (8) is rewritten as follows:

$$Z_t = \begin{bmatrix} \bar{Y} & 0 \\ 0 & \bar{Y} \end{bmatrix} = I_2 \otimes \bar{Y}, \text{ where } \bar{Y} = [1, Y_{1,t-1}, Y_{2,t-1} \cdots Y_{1,t-p}, Y_{2,t-p}] \tag{14}$$

Then, substitute (9) and (14) into (10), yielding:

$$\begin{aligned}\Phi_{GLS} &= [(I_2 \otimes \bar{Y})'(V \otimes I_T)^{-1}(I_2 \otimes \bar{Y})]^{-1}(I_2 \otimes \bar{Y})'(V \otimes I_T)^{-1}Y \\ &= [I_2 \otimes (\bar{Y}'\bar{Y})^{-1}\bar{Y}']Y \\ &= \begin{bmatrix} (\bar{Y}'\bar{Y})^{-1}\bar{Y}'Y_{1t} \\ (\bar{Y}'\bar{Y})^{-1}\bar{Y}'Y_{2t} \end{bmatrix} = \begin{bmatrix} \Phi_{1,OLS} \\ \Phi_{2,OLS} \end{bmatrix}\end{aligned}$$

It is shown that the SUR estimator in the VAR system reduces to a single-equation OLS estimator. Therefore, in most situations, identical results can be obtained by estimating each equation using the OLS method separately, which is why the OLS estimator is so popular. It is worth noting that equations in a VAR system do not always have identical regressors, such as when the null hypothesis (4) is true, which is of concern. Then, (8) can be rewritten as follows:

$$Z_t = \begin{bmatrix} 1, Y_{1,t-1}, \cdots Y_{1,t-p}, & \cdots 0 \cdots \\ \cdots 0 \cdots & 1, Y_{1,t-1}, Y_{2,t-1} \cdots Y_{1,t-p}, Y_{2,t-p} \end{bmatrix} \tag{15}$$

According to the Gauss–Markov theorem, in this situation, SUR estimator is more efficient than the OLS estimator. The larger the correlation between the error terms, the larger is the efficiency gain the SUR can achieve relative to the OLS. This is an important point. Mackinnon (2002) argued that the null hypothesis must be satisfied by the bootstrap data generating process, which means bootstrap resampling should be performed under the null hypothesis. Thus, when constructing bootstrap samples, it is necessary to resort to the SUR method in order to utilize information on the correlation between error terms. In other words, the SUR estimator should be adopted to generate the bootstrap sample recursively. In practice, Σ is usually unknown and, thus, is replaced by an alternative estimate $\hat{\Sigma}$:

$$\hat{\Sigma} = \begin{bmatrix} \hat{\sigma}_{11}, & \hat{\sigma}_{12} \\ \hat{\sigma}_{12}, & \hat{\sigma}_{22} \end{bmatrix} \tag{16}$$

where $\hat{\sigma}_{ij} = (\sum_{t=1}^{T} \Sigma \hat{e}_{it}\hat{e}_{jt})/T$, and $\hat{e}_{it}$ is the residual of the OLS estimation for equation i. Then, $\hat{\Sigma}$ is a consistent estimate for Σ. The method using $\hat{\Sigma}$ is called the feasible GLS (FGLS) method.

3.3 Bootstrap SUR Granger Causality Test Procedure

The basic principle of the bootstrap SUR Granger causality test is to generate bootstrap samples under the null hypothesis and then to perform the standard Granger causality test many times.

STEP 1: Use an information criterion to determine the optimal lag length p of the VAR system.

STEP 2: Perform the Granger causality test using VAR(p) and obtain the Wald statistic W.

STEP 3: Use the FGLS method to estimate VAR(p) under the null hypothesis. Thus, the SUR estimator of the coefficients $\hat{\Phi}_0,\ \hat{\Phi}_1, \ldots, \hat{\Phi}_p$ can be obtained, as can the residuals $\hat{\varepsilon}_1, \ldots, \hat{\varepsilon}_T$ and residual deviations $\hat{\varepsilon}_1 - \bar{\hat{\varepsilon}}, \ldots, \hat{\varepsilon}_T - \bar{\hat{\varepsilon}}$. Here, $\hat{\varepsilon}_i$ are 2×1 vectors containing information on the contemporaneous correlation of the error terms, and $\bar{\hat{\varepsilon}}$ is the average of $\hat{\varepsilon}_i$. As mentioned above, owing to the two equations having different regressors in VAR(p), the SUR estimator is more efficient than OLS estimator.

STEP 4: Draw T samples, with replacement, from the residuals deviations $\hat{\varepsilon}_1 - \bar{\hat{\varepsilon}}, \ldots, \hat{\varepsilon}_T - \bar{\hat{\varepsilon}}$ to form a bootstrap residual sample $\varepsilon_1^*, \ldots, \varepsilon_T^*$.

STEP 5: Combine the initial values of $Y_1, \ldots, Y_p$, the coefficient estimator $\hat{\Phi}_0,\ \hat{\Phi}_1, \ldots, \hat{\Phi}_p$, and the bootstrap residual sample $\varepsilon_1^*, \ldots, \varepsilon_T^*$ in order to calculate the bootstrap samples Y^* recursively.

STEP 6: Use bootstrap sample Y^* to perform the Granger test and to obtain the bootstrap Wald statistic W^*.

STEP 7: Repeat steps 3 to 6 a certain times (here, 1000 times) in order to obtain a series of bootstrap statistics W^* and their empirical distribution. The α-level bootstrap critical value W_α is taken from the $(1-\alpha)th$ quantile of this empirical distribution. Note that if $W > W_\alpha$, then the null hypothesis should be rejected.

4 Data and Empirical Analysis

4.1 Data Sources

The nominal GDP and electricity consumption data for China are obtained from the China National Bureau of Statistics. Although electricity consumption data are published every month, GDP data are published seasonally. Therefore, the paper uses the seasonal data for both. The earliest time when seasonal GDP can be obtained is 1992Q1. These data cover the period from 1992Q1 to 2016Q2 (Fig. 1). This is a relatively large sample compared with those of previous time-series empirical studies (Shiu and Lam 2004; Yuan et al. 2007).

The nominal GDP data is deflated into real one by a seasonal real GDP growth index (adopting 1992Q1 as a base period) and the seasonal effect is removed by X12 procedure. Figure 2 shows the real GDP series. As shown, the earlier part of the sample period exhibits a relatively low economic growth rate. However, from 2000, China's

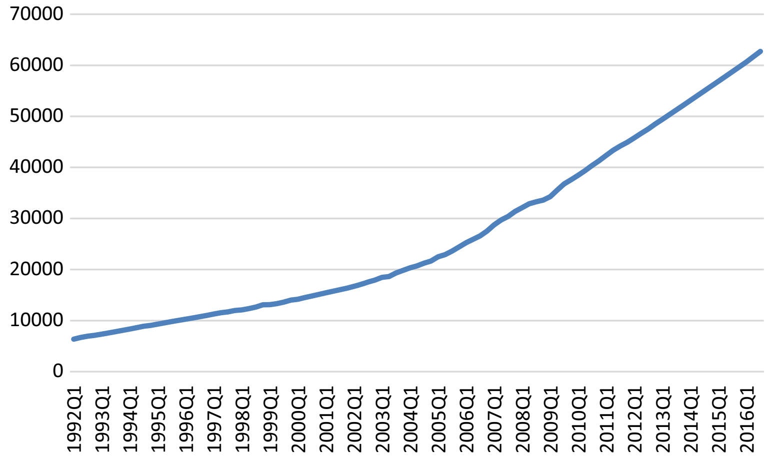

Fig. 1 Seasonally adjusted GDP in China for 1992Q1–2016Q3

economy began to accelerate, becoming the sixth largest economy in the world in the same year. Five years later, China had outgrown France and the United Kingdom, ranking fourth in the world. By 2009, the Chinese economy had become the second largest in the world, overtaking those of Germany and Japan.

In 2011, China's electricity generation exceeded that of the United States, and has remained the highest in the world since then. In 2015, the country's electricity generation reached 56,184 billion Kwh, a slight decrease of 0.2% from the previous year. Nevertheless, the total electricity generation now exceeds that of the United States and Japan, combined. Huge quantities of electricity consumption in China have caused many problems, including carbon emissions (Song and Zhou 2015; Wang et al. 2015). In the following empirical studies, monthly data of electricity consumption are converted into quarterly data, by accumulation, and then the seasonal effect is removed by X12 procedure. Figure 2 shows the trend of electricity consumption in China. During 1999–2000, the growth rate of electricity consumption is low (about 7.5% per year). However, after 2000, the electricity consumption began to accelerate owing to the heavy industrialization. From 2000–2008, the growth rate reached 13.2% per year. The 2008 world financial crisis knocked back China's economic growth and, consequently, electricity consumption as well. Since then, electricity consumption in China has fluctuated significantly. As is usual in such studies, the two variables used in the following empirical investigation are transformed to natural logarithm form.

4.2 Empirical Results

Before detecting the causality relationship between electricity consumption and economic growth, the stationary property of the variables needs to be examined. If variables are stationary, bootstrap method is no longer needed. The ADF test is adopted to examine the stationarity. Considering the goal is not equation estimation, the Ljung-Box Q-statistic is employed, which ensures there is no residual serial correlation by

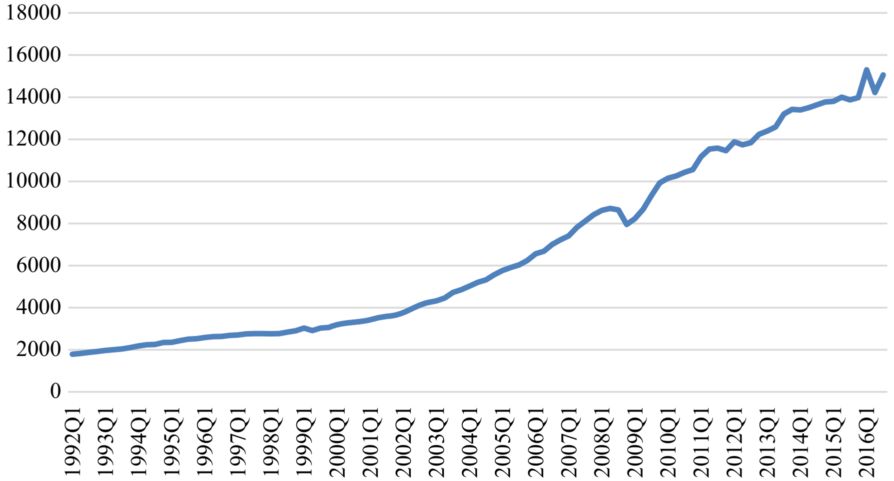

Fig. 2 Seasonally adjusted electricity consumption in China for 1992Q1–2016Q3

Table 1 Unit root test results

Variables	ADF					PP
	t-stat.	Lag	Ljung–Box Q-stat.			t-stat.
			Q(1)	Q(2)	Q(3)	
Y	−0.696	1	0.322	2.069	2.697	−1.342
E	−1.193	1	0.002	0.931	0.998	−1.341
ΔY	−5.251***	1	4.2e−05	0.354	1.398	−7.650***
ΔE	−6.060***	1	0.002	0.014	0.226	−9.970***

*** Denotes the null hypothesis can be rejected at the 1% significance level. For level variables, test models contain constant and trend terms, and the 1, 5, and 10% critical values are −4.047, −3.453, and −3.152, respectively. For difference variables, the test models contain a constant, and the 1, 5, and 10% critical values are −3.516, −2.893, and −2.582, respectively. The null hypothesis in all cases is that the variable is nonstationary

selecting the appropriate lag order. The PP test (Phillips and Perron 1988) is also conducted, for robustness. Table 1 contains the results of the unit root test, and shows that the level variables are nonstationary. However, the first differences of the two variables are stationary. In each test, the null hypothesis is rejected at the 1% significance level. Given these results, it is concluded that the data generating process is characterized by one unit root.

Because the electricity consumption and GDP are found to be I(1) processes, it is likely that the two series have a common trend over the long term, or are cointegrated. The Johansen test, proposed by Johansen based on a maximum likelihood estimation (Johansen 1988; Johansen and Juselius 1990), is used to check this trend between them. Before equation estimation, the optimal lag number of the VAR systems needs to be determined. The Akaike information criterion (AIC) supports that the lag order should be three. Thus, a lag order of two is used in the Johansen test. Table 2 presents

Table 2 Johansen cointegration test results

Maximum rank	Trace statistic	5% Critical value	1% Critical value
0***	35.894	15.41	20.04
1	0.635	3.760	6.650

*** Denotes the null hypothesis can be rejected at the 1% significance level

the test results. As shown, the null hypothesis of no cointegration is rejected at the 1% significance level. However, the null hypothesis of only one relationship cannot be rejected at the 1% significance level. Therefore, it is confirmed that there is a long-run relationship between electricity consumption and GDP.

Given that there is a cointegration relationship between the electricity consumption and GDP, there should be a Granger causality in at least one direction (Engle and Granger 1987). Thus, it is needed to detect the direction of Granger causality. The paper performs the bootstrap SUR Granger test for all samples, as well as for the subsamples of different periods. Owing to the imbalance between the electricity supply and demand in the 21st century, the samples are divided into three subsamples to examine the possible structural changes between electricity consumption and GDP. The first subsample runs from 1992Q1 to 1999Q4, which is a light industrialization period. The second subsample runs from 2000Q1 to 2008Q4, which is the early stage of heavy industrialization. The third subsample covers the period 2009Q1–2016Q3, during which China's economy entered a new normal. As mentioned previously, the lag order is set to three in the VAR system for all bootstrap SUR Granger tests.

Table 3 gives the results of the bootstrap SUR Granger tests. As shown, at the 1% significance level, the null hypothesis that GDP does not Granger cause electricity consumption is rejected, but the null hypothesis that electricity does not Granger cause GDP is not able to be rejected. At the 5% significance level, both null hypotheses can be rejected. With regard to the three subsamples, only during the period 2009Q1–2016Q3 can null hypothesis that GDP does not Granger cause electricity consumption be rejected, at the 1% significance level. For the remaining subsamples, the null hypotheses are not able to be rejected at the 1% significance level. However, at the 5% significance level, Granger causality from GDP to electricity consumption is evident during the light industrialization period. Even at the 10% significance level, no any causality is found during the period of heavy industrialization. In the full sample and each subsample, the Wald statistics under the null hypothesis that GDP does not Granger cause electricity consumption are greater than those under the null hypothesis that electricity consumption does not Granger cause GDP. The former is 3–7 times greater than the latter, meaning the power of using GDP to predict electricity consumption is stronger than when using electricity consumption to predict GDP, given that the differences in bootstrap critical values at all significance levels are relatively small.

For the sake of comparison, the paper uses the standard Granger test, the modified Granger test, and the bootstrap SUR Granger test to examine the direction of causality. The first section shows that the standard Wald statistics are 34.067 and 13.180 under

Table 3 The result of bootstrap SUR Granger tests

Period	Null hypothesis	Wald statistic	Bootstrap critical values		
			10%	5%	1%
1992Q1–2016Q3	$Y \neq> E$	34.067***	9.751	12.205	18.080
	$E \neq> Y$	13.180**	7.535	9.768	15.273
1992Q1–1999Q4	$Y \neq> E$	25.242**	15.935	19.687	30.148
	$E \neq> Y$	4.779	8.381	10.621	17.458
2000Q1–2008Q4	$Y \neq> E$	2.046	16.166	19.512	30.689
	$E \neq> Y$	0.739	10.520	13.679	22.366
2009Q1–2016Q3	$Y \neq> E$	37.319***	13.659	17.331	25.802
	$E \neq> Y$	4.165	9.656	12.588	18.895

*** Denotes the null hypothesis can be rejected at the 1% significance level; ** denotes the null hypothesis can be rejected at 5% significance level; * denotes the null hypothesis can be rejected at 10% significance level

Table 4 Comparison of three Granger causality tests

Null hypothesis	$Y \neq> E$	$E \neq> Y$
Standard Wald statistic	34.067	13.180
Modified Wald statistic	39.350	8.610
Asymptotic distribution-$\chi^2(3)$		
1% asymptotic critical value	11.345	11.345
5% asymptotic critical value	7.815	7.815
10% asymptotic critical value	6.251	6.251

the different null hypotheses. The second section shows the modified Wald statistics, which are 39.350 and 8.610 under the different null hypotheses. The third section shows the critical values of the asymptotic distribution. It can be seen that each of the standard Wald statistics is big enough to reject the relevant null hypothesis. The asymptotic critical value at the 1% significance level is only 11.345. Therefore, the standard Granger test gives a bi-directional Granger causality link between electricity consumption and GDP. However, at the 1% significance level, the modified Wald statistics cannot reject the null hypothesis that electricity consumption Granger causes GDP, meaning there is a unidirectional Granger causality between the two. The third section refers to the asymptotic critical values for the standard and modified Granger test, which are lower than the bootstrap critical values at all significance levels. In summary, similar to the bootstrap SUR Granger test, the modified Granger test shows a unidirectional causality from GDP to electricity consumption. Conversely, electricity consumption is not a leading indicator of economic growth (Table 4).

Although the bootstrap method is generally considered more reliable, the same inferences are obtained as those of the modified Granger test based on the asymptotic test. If a 5% or 10% significance level is allowed, even the standard Granger test shares the same results as the bootstrap SUR Granger test. A statistical inference based on asymptotic theory is not always misleading; however, it does not ensure that the asymptotic test is reliable (Mackinnon 2002).

4.3 Result Discussion

According to the empirical analysis, a strong and obvious causality from GDP to electricity consumption is found. However, the causality relationship from electricity consumption to GDP is relatively weak. At least at the 1% significance level, there is no such causality relationship in the full sample test. In the three subsample tests, no causality relationship from electricity consumption to GDP is found, even at the 10% significance level. These results are different from the preceding empirical results, by Shiu and Lam (2004) and Yuan et al. (2007), who argued that the direction of causality is from electricity consumption to GDP. This difference can be attributed to method and samples adopted in respective studies. As mentioned by Mackinnon (2002), tests based on bootstrap techniques usually have more reliable results than that of asymptotic theory. Therefore, the paper provided the fresh evidence from a more robust methodological framework. Using the annual data, the results of previous studies primarily reflected the business cycle in a long period, not the dynamic response relationship in a relatively short term.

Analysis based on subsamples shows there is no Granger causality relationship between the two variables in 2000Q1–2008Q4. The paper provides two explanations for this. One is the “vertical dual pricing system” in the electricity industrial chain (Yu and Wang 2008; Song et al. 2015), which means that the upstream coal price is determined by the market, while the downstream electricity price is determined by the government. From 2000 to 2008, China’s economy was booming, and the GDP growth rate maintained was in the double digits, causing the prices of many products to rise rapidly. Datong high-quality mixed coal at Qinhuangdao rose by as much as 245%. However, the electricity price cannot increase accordingly, which disturbs the plans of electricity producers. In this period, electricity brownouts occurred frequently across China. Other than this period, the coal price was relatively stable and the “vertical dual pricing system” did not cause a serious problem.

The second explanation has to do with the limiting of electricity generation capacity. Apart from the price factor, installed capacity and investments by the electricity industry affect electricity consumption. In 1998, there was a large surplus of electricity in China, owing to the Asian financial crisis, which had an impact on subsequent electricity industry development. Since then, electricity investment has been strictly limited by China’s central government. The growth rate of power plants in China was only 6% from 1998 to 2001. However, after 2000, China’s economy began to boom. The growth rates of electricity consumption in 2000, 2001, and 2002 were 11, 8.3, and 11.4% respectively, which caused the first round of electricity brownouts in 2002. From then on, China’s government resorted to encouraging investment in the electricity industry, and power plant construction began to accelerate. Owing to capital, risk, and monopoly factors, among others, many professionals believe that the real growth rate of installed capacity is lower than expected. China experienced an electricity shortage until the global financial crisis in 2008. The constraints of installed capacity may deter electricity consumption from responding to economic growth. This is verified by the results for subsample 2009Q1–2016Q3.

4.4 Policy Implication

The previous studies using China's annual data can capture the relationship of economic recycle within years. In contrast, this study with the use of quarterly data has better policy implication. Specifically, the variation in GDP is three quarters ahead of the variation in electricity consumption. This is particularly meaningful for China's electricity producers. The electricity price in China is still set by the government, it lasts 30 years since the economic reform is open to the market. Having the government control the electricity price can avoid price fluctuation risk. However, it is not able to send information of demand and supply in the electricity market. Thus, it is impossible for electricity producers to depend on the price signal to arrange a generation plan. However, GDP values of the past three quarters contain information on electricity demand, which can be used by the electricity producers to adjust their production plans.

Furthermore, it is found that electricity is not a good indicator of the future economy. If there were a dramatic increase in electricity consumption, it would seem dangerous to predict growth in GDP in subsequent periods. Nevertheless, electricity consumption is a useful indicator to check the reliability of GDP data due to the cointegration relationship. If the statistics show that electricity has increased, it is worth to check whether GDP is growing overall. If not, this may indicate that the GDP statistics are problematic. For example, published data show that economic growth in Liaoning in the first three quarters of 2016 was -2.2%. These data caused a negative reaction in the media to Liaoning. However, during this period, the electricity consumption is positive (0.93%), which, based on this research, is clearly in contradiction with cointegration relationship. In a survey of the Liaoning CPPCC research group, it is found that the standard used by the Liaoning statistical department had been changing since the beginning of 2016, which affected the accuracy of the GDP statistical data in Liaoning rather seriously.

5 Conclusion

This study suggested a new Granger causality test method for an empirical investigation into the nexus of electricity consumption and economic growth. It combines the bootstrap method and the SUR estimator in order to consider the contemporaneous correlation of the error term in the VAR system. Based on data for China for the period 1992Q1–2016Q3, the empirical results of a cointegration test showed that a long-run relationship exists between electricity consumption and economic growth. Thus, electricity consumption can be treated as an alternative indicator when monitoring economic activity. There is a unidirectional Granger causality running from GDP to electricity consumption at the 1% significance level, while the causality relationship from electricity consumption to GDP is relatively weak. Therefore, caution needs to be exercised in using electricity consumption to predict future economic activity. Study results show that GDP is a leading indicator (about three quarters) for electricity consumption fluctuation. It means, in practice, electricity producers can make their electricity generation plans according to past GDP fluctuation.

This study provides an alternative bootstrap method for estimating the distribution of statistic in Granger Causality test. However, this work is limited with the lack of a Monte Carlo simulation experiment to assess the size and power property. Monte Carlo experiments on bootstrap method are usually computationally expensive, involving both Monte Carlo replications and bootstrap replications. The future research will deal with the detail design of such experiments, which is expected to give interesting evidence.

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