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Forecast of electricity consumption and economic growth in Taiwan by state space modeling

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ABSTRACT

This paper investigates the Granger causality between electricity consumption (EL) and economic growth for Taiwan during 1980–2007 using the cointegration and error-correction models. The results indicate that EL and real GDP are cointegrated, and that there is unidirectional short and long run Granger causality from economic growth to EL but not vice versa. Considering cointegrated property, this study proposes a new error-correction state space model (ECSTSP) with the error-correction term (ECT) in its state vector to forecast both EL and real GDP simultaneously, whereas the ECM is not in the state vector of classical state space model (STSP). The out-of-sample forecasting ability of the ECSTSP is compared with STSP and SARIMA models using six forecasting horizons from 1-year to 6-year. The results suggest that all of the models have strong forecasting performance with MAPE less than 5.4%, but the ECSTSPs have the smallest average values of MAPEs for both EL and GDP, which are 2.50% and 1.74%, respectively. For short-term predictions, SARIMA models are as good as STSP or ECSTSP ones. For long-term prediction, ECSTSP is the best model, because the cointegration relationship between real GDP and EL is taken into account in this model.

1. Introduction

Energy is the foundation of economic development. Electricity is the most flexible form of energy and constitutes one of the vital infra-structural inputs in socioeconomic development. Both economy and energy consumption in Taiwan have been growing rapidly. In the 1990s, energy consumption increased about 5% per year, with real GDP growing at an average annual rate of about 5.4%. Among the categories of energy consumed, electricity took up 52%, petroleum 38%, and the rest 10%. Total electricity consumption (EC) rises sharply from 82.60 billion (kwh) in 1990 to 229.20 billion (kwh) in 2007, implying an annual growth rate of 6.19%. Official energy projections for Taiwan indicate a continuing increase in demand for energy, especially for electricity, in the next two decades (Bureau of Energy, Ministry of Economic Affairs in Taiwan).

There are numerous studies that deal with the causality relationship between EC and economic growth. This study tried to focus on studies conducted in the recent five years, i.e., 2004 and afterwards, especially regarding countries with developing economies, such as Taiwan. These studies are summarized in Table 1. The findings from the studies vary not only across countries but also across methodologies for the same country. In a summary of the literature on the causal relationship between EC and economic growth, there is evidence to support bidirectional or unidirectional causality, or no causality, between EC and economic growth.

Evidence in either direction will have a significant bearing on policy. If, for example, there is unidirectional causality running from economic growth to EC, it could imply that electricity conservation policies may be implemented with little or no adverse effect on economic growth. Unidirectional causality running from economic growth to EC was revealed by Ghosh [1] for India, by Mozumder and Marathe [2] for Bangladesh, by Narayan and Smyth [3] for Australia, by Yoo [4] for Indonesia and Thailand, and by Chen et al. [5] for Korea, Singapore, India, Malaysia and the Philippines.

In contrast, if a unidirectional causality runs from EC to economic growth, reducing EC could lead to a fall in economic growth while increasing it may contribute towards a country's economic growth. Unidirectional causality running from EC to economic growth was revealed by Shiu and Lam [6] and Yuan et al. [7] for China, by Wolde-Rufael [8] for Shanghai, China, by Ho and Siu [9] for Hong Kung, by Altinay and Karagol [10] for Turkey, by Lee and Chang [11] for Taiwan, and by Chen et al. [5] for Indonesia.

On the other hand, if bidirectional causality is found, economic growth may demand more electricity whereas more EC may induce economic growth. EC and economic growth may complement each other and energy conservation measures may negatively affect economic growth. For example, Jumbe [12] for Malawi, Tang [13]

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Table 1
Empirical results from causality tests between electricity consumption and economic growth for developing countries.

Author	Country	Method	Period	Finding
Mozumder and Marathe [2]	Bangladesh	VECM	1971–1999	GDP → EL
Narayan and Smyth [3]	Australia	VECM	1966–1999	GDP → EL
Yoo [4]	Thailand	Hsiao's version of GC	1971–2002	GDP → EL
	Indonesia			GDP → EL
	Malaysia			GDP ↔ EL
	Singapore			GDP ↔ EL
Chen et al. [5]	Korea	VECM	1971–2001	GDP → EL
	Singapore	Panel VECM		GDP → EL
	India			GDP → EL
	Malaysia			GDP → EL
	Philippines			GDP → EL
	Indonesia			GDP ← EL
	China			GDP o EL
	Taiwan			GDP o EL
	Thailand			GDP o EL
	Hong Kong			GDP ↔ EL
	10 Asian countries			GDP ↔ EL
Shiu and Lam [6]	China	VECM	1971–2000	GDP ← EL
Yuan et al. [7]	China	VECM	1978–2004	GDP ← EL
Wolde-Rufael [8]	Shanghai, China	TY version of Granger non-causality	1952–1999	GDP ← EL
Ho & Siu [9]	Hong Kong	VECM	1966–2002	GDP ← EL
Altinay and Karagol [10]	Turkey	GC and VAR	1950–2005	GDP ← EL
Lee and Chang [11]	Taiwan	Weak exogeneity	1954–2003	GDP ← EL
Jumbe [12]	Malawi	GC & VECM	1970–1999	GDP ↔ EL
Tang [13]	Malaysia	GC	1972–2003	GDP ↔ EL
Morimoto and Hope [14]	Sri Lanka	Regression	1960–1998	GDP ↔ EL
Zachariadis & Pashourtidou [15]	Cyprus	VECM	1960–2004	GDP ↔ EL
Yoo [16]	Korea	VECM	1970–2002	GDP ↔ EL

Note: GC and GNC indicate the Granger causality and Granger non-causality tests, respectively. GDP o EL indicates no causality between GDP and EL.

and Yoo [4] for Malaysia, Yoo [4] for Singapore, Morimoto and Hope [14] for Sri_Lanka, Zachariadis and Pashourtidou [15] for Cyprus, Yoo [16] for Korea, Yang [17] for Taiwan, and Chen et al. [5] for Hong Kong found bidirectional causality between EC and economic growth. In addition, Chen et al. [5] found bidirectional causality for 10 Asian countries using panel data.

Finally, no causality in either direction would indicate that energy conservation policies may not affect economic growth, and rise in real income may not affect EC. Chen et al. [5] found that there was no causality between economic growth and EC in China, Taiwan and Thailand.

Recently, various studies have been conducted to explore the causality relationship between total energy consumption and economic growth in Taiwan ([11] and [17–20]). Although the EC is an important category constituting 52% of the total energy consumption in 2007, there are very few studies concerning the relationship between electricity use and GDP for Taiwan. In articles [5,11,17], different results were provided by using annual data sets from 1971 to 2001, 1954 to 2003 and 1954 to 1997, respectively. Furthermore, to the best of our knowledge, there is no study to jointly forecast both EC and real GDP dynamically, using the results of causality relationship studies and quarterly data sets.

The two purposes of this study are as follows. The first one is to investigate the causality relationship between EC and economic growth, and to obtain policy implications from the results. This purpose is accomplished by the following steps: First, stationarity and cointegration are tested; second, error-correction models are estimated to test for the Granger causality; finally, the *F*-tests are performed to determine the joint significance levels of causality between the two variables.

The second purpose is to construct a new error-correction state space model (ECSTSP hereafter) for forecasting of both EC and real GDP simultaneously, taking the cointegration property into account. For modeling and forecasting time series, univariate Box–Jenkins ARIMA [21] linear models are used. Recently, some univariate nonlinear models have been proposed. Pappas et al. [22,23] proposed an adaptive method based on the multi-model partitioning filter for short-term electricity load forecasting. Azadeh [24] presented an integrated algorithm based on ANN, simulated-based ANN, time series and DOE (ANOVA and DMLT) to forecast monthly electricity in Iran. Lauret [25] proposed the use of Bayesian regularization as a technique to estimate the parameters of a neural network in order to forecast load. For long-term forecasting, Pao [26] proposed an ANN to forecast electricity market pricing. Articles [27] and [28] presented a trigonometric grey prediction approach and a grey prediction with rolling mechanism approach to forecast electricity demand in China and Turkey, respectively. On the other hand, the multivariate models of neural network techniques [29,30], regression and econometric approach [31–33] have been also applied in predicting EC. Karanfil and Ozkaya [34] utilized the Kalman Filter technique for GDP forecasting in Turkey. Furthermore, Jebaraj and Iniyan [35] made a literature survey in order to give a brief overview of different types of energy modeling and forecasting.

This paper is organized as follows. The next section outlines the econometric methodology and models. Section 3 presents the data source, shows the empirical results and makes model comparisons. Section 4 provides the discussion and policy implications. The final section summarizes this work and concludes.

2. Methodology

According to Engle and Granger [36], a linear combination of two or more nonstationary series (with the same order of integration) may be stationary. If such a stationary linear combination exists, the series are considered to be cointegrated and long run equilibrium relationship exists. Incorporating these cointegrated properties, the error-correction model (ECM) is specifically adopted to examine the Granger causality among variables. Taking the cointegration property into account, this study proposes a new ECSTSP to forecast both EC and real GDP simultaneously. The out-of-sample forecasting ability of ECSTSP is compared with both the state space model (STSP) and SARIMA, where STSP and SARIMA are the multivariate and univariate benchmark models, respectively.

2.1. Granger causality, stationarity and cointegration

Since the use of the ECM requires the series to be cointegrated with the same order, it is essential to first test the series for stationarity and cointegration. The Augmented Dickey-Fuller [37] (ADF) and the Phillips-Perron [38] (PP) unit root tests are used to investigate the stationarity and the order of integration of the variables. If a nonstationary series has to be differenced d times to become stationary, then it is said to be integrated of order d: i.e., $I(d)$. The differenced data is to be applied for the causality test.

When both series are integrated of the same order, The Johansen maximum likelihood method [39,40] is used to test cointegration. The evidence of cointegration rules out the possibility that the estimated relationship is spurious. The existence of cointegration indicates that there are long run equilibrium relationships among the variables, and thereby Granger causality among them in at least one direction (Engle and Granger [36] and Oxley and Greasley [41]). The ECM is used for correcting disequilibrium in the cointegration relationship, captured by the error-correction term (ECT), as well as testing for long and short run causality among cointegrated variables. The ECM is specified as follows:

$$\Delta X_t = \alpha + \sum_{i=1}^{m} \beta_i \Delta X_{t-i} + \sum_{j=1}^{n} \gamma_j \Delta Y_{t-j} + \delta \mathrm{ECT}_{t-1} + \mu_t \tag{1}$$

$$\Delta Y_t = a + \sum_{i=1}^{q} b_i \Delta X_{t-i} + \sum_{j=1}^{r} c_j \Delta Y_{t-j} + d\mathrm{ECT}_{t-1} + \nu_t, \tag{2}$$

where X_t and Y_t represent the EL and real GDP in actual or logarithmic form respectively, and $(\Delta X_t, \Delta Y_t)$ are the differences in these variables that capture their short run disturbances. The μ_t, ν_t are the serially uncorrelated error terms. The ECT_{t-1} is derived from the long run cointegration relationship. This specification can test the short and long run causality among co-integrated variables. The optimum lag lengths m, n, q and r are determined bases on Akaike's [42] information (AIC) and Schwarz Bayesian (SBC) criteria.

2.2. SARIMA model

The SARIMA model analyzes and forecasts equally spaced univariate seasonal time series data. It predicts a value in a response time series as a linear combination of its own past values and past errors. The analysis performed by SARIMA procedure is divided into three stages: identification, estimation and diagnostic checking, and forecasting, which correspond to the stages described by Box and Jenkins. Classical Box–Jenkins models describe stationary time series. Thus, in order to tentatively identify a Box–Jenkins model, we must first transform the time series into a stationary time series by taking a pre-differencing transformation. The seasonal Box–Jenkins models, SARIMA $(p,d,q)\otimes(P,D,Q)_S$, are expressed as follows:

where

$$\begin{aligned}
&\phi_p(B)\Phi_P\left(B^S\right)(1-B)^d\left(1-B^S\right)^D y_t = \delta + \theta_q(B)\Theta_Q\left(B^S\right)a_t \\
&\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \\
&\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B_q \\
&\Phi_P\left(B^S\right) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \cdots - \Phi_P B^{PS} \\
&\Theta_Q\left(B^S\right) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \cdots - \Theta_Q B^{QS}
\end{aligned} \tag{3}$$

In this expression, the time series is y_t; S is the seasonal periodicity; B is the backward shift operator; d is the order of regular differences; D is the order of seasonal differences, and a_t, a_{t-1},... are independent random shocks. The series a_t is assumed to be a white noise process, and $\phi_p(B)$ and $\theta_q(B)$ are polynomials in B of order p and q respectively. The roots of $\phi_p(B) = 0$ and $\theta_q(B) = 0$ should lie outside the unit circle.

2.3. STSP model

STSP modeling was introduced by Kalman [43] and is known as Kalman filtering. It is appropriate for jointly forecasting several related time series that are dynamically interacting. Taking the autocorrelations among the whole set of variables into account, the SAS STATESPACE may give better forecasts than methods that model each series separately [44]. The methods used in the STATESPACE procedure are described in Akaike [42]. These methods assume that the time series are jointly stationary. Nonstationary series must be made stationary by some preliminary transformation, usually by differencing. If the stationary multivariate time series, x_t, of dimension r is taken into account, where $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{r,t})$, a STSP model for this multivariate time series could be written as:

$$z_t = Fz_{t-1} + Ge_t \tag{4}$$

where z_t is a state vector of dimension s, whose first r components compose x_t and whose last $s-r$ elements are conditional predictions of future x_t, for example, $z_t = (x_{1,t}, x_{2,t}, x_{3,t}, x_{1,t+1|t}, x_{3,t+1|t}, x_{1,t+2|t})'$. F is an s-by-s transition matrix. G is an s-by-r input matrix, with the identity matrix I_r forming the first r rows and columns. e_t is a sequence of independent normally distributed random vectors of dimension r with mean 0 and covariance matrix Σ_{ee}. Even though the variables have been differenced for stationarity, STATESPACE procedure forecasts them in their non-differenced levels.

In this study, the STSP model would be employed for forecasting of both EL and real GDP interrelated time series with a feedback relationship, if a cointegration relationship exists between the two variables. The proposed new ECSTSP model includes ECT in its state vector, where ECT is derived from the cointegrating vector. However, the state vector of classical STSP model does not include ECT. The state vector z_t of ECSTSP has dimension s, whose first 3 elements are x_t, $x_t = (\Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_t, \Delta\mathrm{ECT}_t)$, whose last s-3 elements are conditional predictions of future x_t, for example, $z_t = (\Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_t, \Delta\mathrm{ECT}_t, \Delta\mathrm{EL}_{t+1|t}, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+2|t})'$. The transition matrix F has dimension sxs. The input matrix G has dimension $sx3$, with the identity matrix I_3 forming the first 3 rows and columns.

3. Data and experimental results

3.1. Data analysis

The data provided cover the period from 1980 to 2007 (sample period 1) with each data point representing EL (Fig. 1) and real GDP (Fig. 2) for each quarter. All data are taken from the AREMOS economic-statistic data banks, created by the Ministry of Education in Taiwan. The sub-period from 1990 to 2007 (sample period 2) is employed to confirm the parameter stability in estimating the ECM. Both series EL and GDP appear to be nonstationary in level. As shown in Fig. 1, the EL data show strong seasonality and growth trends. The electricity peak season for each year generally occurs in July to September, because electricity use is greatest in the summer. The troughs of these two series fall in the fourth season of each year, which contains many Chinese holidays and vacations.

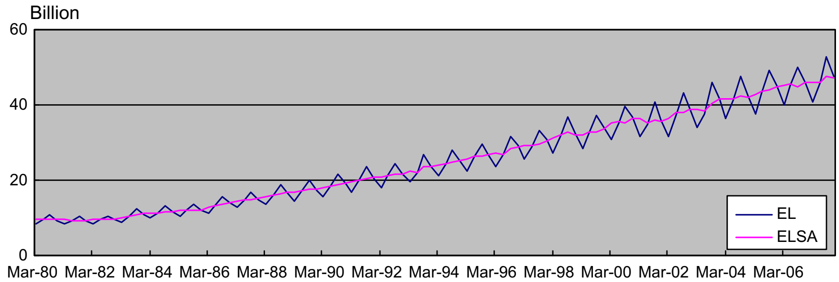

Fig. 1. Electricity consumption from 1980 to 2007 in Taiwan.

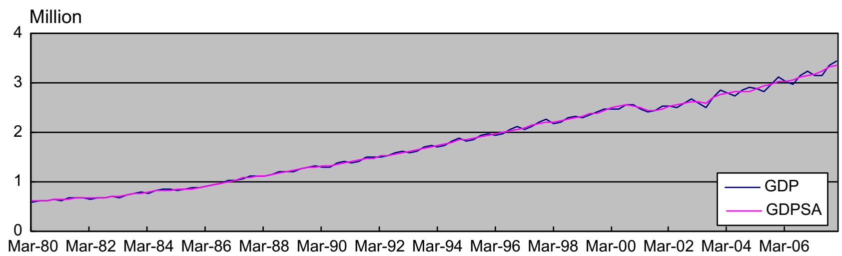

Fig. 2. Real GDP from 1980 to 2007 in Taiwan.

All of the empirical analysis on the relationship between variables has only studies the relationship of the trend [7], seasonal factors can cause a biased estimator. Thus, this study uses the X-12-ARIMA Seasonal Adjustment Program [45] to remove seasonal effects from both EC and real GDP quarterly data sets. The resulting seasonally adjusted ELSA and GDPSA time series are also shown in Figs. 1 and 2, respectively. The descriptive statistics of EL, ELSA, GDP, and GDPSA variables are reported in Table 2 for both sample periods 1 and 2.

3.2. Results of unit roots, cointegration and Granger causality tests

In this analysis, the order of integration of data is investigated. In order to avoid the biased estimator caused by seasonal factors, seasonally adjusted variables are used in the models. They are LELSA and LGDPSA, the natural logarithms of ELSA and GDPSA. The logarithm variables have economic meaning because they are regarded as the growth of the respective differenced variables. For sample period 1, panel A of Table 3 presents the results of the ADF and PP unit root tests on the levels and the first differences of both LELSA and LGDPSA variables. In addition to LELSA and LGDPSA variables, the unit root tests of both EL and GDP variables are shown in panel B of Table 3, for the STSP forecasting model to use in sample period 2. Results of both the ADF and the PP tests indicate that all of the series are nonstationary. However, first differences of these four series lead to stationarity. This result indicates that all of the variables in Table 3 are of order one, i.e., $I(1)$.

Given that the employed series are of the same order of integration, the next step is to test whether the two series LELSA and LGDPSA are cointegrated over the two sample periods. Table 4 shows the results of the Johansen test. The trace and eigenvalue tests reject both the hypotheses of no cointegrating equation and of at most one cointegrating equation at 5% level of significance over the sample period 1. This implies that there are two cointegrating equations at 5% level of significance. However, only one cointegrating equation of the two is consistent [46]. The trace and eigenvalue tests also reject the hypothesis of no cointegrating equation at 5% level of significance over the sample period 2. Table 4 shows that the estimated cointegrating vectors normalized with respect to LELSA are (1.00, 1.163) and (1.00, 1.220) for both sample periods. The results shown in panel B of Table 4 also indicate that the two series EL and GDP have one cointegration equation with the optimal lag length 4 over the sample period 2 (the hypothesis of no cointegration equation is rejected at 5% level). The estimated cointegrating vectors normalized with respect to EL are (1.00, 23.492). The positive signs of the variables conform to the theory in literature [7], i.e., there is a long-term positive relationship between real GDP and EC for Taiwan. The existence of a cointegrating

Table 2
Descriptive statistics of included variables.

Variables	Usable obs.	Mean	S.D.	Min.	Max.
Panel A: sample period 1980–2007					
EL	116	26,014,980	12,776,311	8,332,261	52,985,000
ELSA	116	25,998,693	12,489,520	9,244,621	48,998,635
GDP	116	1,828,285	848,978.2	593,538	3,440,210
GDPSA	116	1,827,890	847,309.6	613,714	3,377,318
Panel B: sample period 1990–2007					
EL	72	38,589,517	12,173,618	17,515,317	64,305,493
ELSA	72	38,563,734	11,631,932	20,051,444	57,815,522
GDP	72	2,270,806	571,398.5	1,291,437	3,446,720
GDPSA	72	2,270,195	567,335.8	1,312,886	3,345,857

Table 3
Results of ADF and PP unit root tests.

Variables	ADF statistics		PP statistics	
	Levels	First differences	Levels	First differences
Panel A: sample period 1980–2007				
LELSA	−1.118 [1]	−11.592 [0][a]	−1.025 [3]	−11.592 [0][a]
LGDPSA	−2.324 [1]	−6.778 [0][a]	−2.472 [2]	−6.478 [2][a]
Panel B: sample period 1990–2007				
LELSA	−2.810 [1]	−12.588 [0][a]	−2.362 [1]	−12.588 [0][a]
LGDPSA	−2.021 [1]	−6.016 [0][a]	−2.300 [0]	−6.026 [1][a]
EL	0.402 [3]	−17.182 [2][a]	−1.354 [14]	−15.916 [12][a]
GDP	0.586 [4]	−4.107 [4][a]	1.109 [15]	−9.611 [15][a]

Note: Each ADF and PP tests uses an intercept and no trend and leg length has been chosen based on minimum AIC. Fingers in brackets are the lag lengths.
[a] Implies significance at 1% level.

Table 4
Results of Johansen cointegration test.

Eigenvalue	Trace Stat.	5% critical value	Max Eigen. Stat.	5% critical value	Number of cointegration
Panel A: sample period 1980–2007					
Variable: LELSA and LGDPSA; Lags interval: 1–2					
0.207	31.677[a]	12.321	25.289[a]	11.225	None
0.057	6.388[a]	4.130	6.388[a]	4.130	At most 1
Normalized cointegration equation: LELSA = 1.163 × LGDPSA					
Panel B: sample period 1990–2007					
Variables: LELSA and LGDPSA; Lags interval: 1–2					
0.222	18.543[a]	12.321	17.321[a]	11.225	None
0.018	1.221	4.130	1.221	4.130	At most 1
Normalized cointegration equation: LELSA = 1.220 × LGDPSA					
Variables: EL and GDP; Lags interval: 1–4					
0.306	25.295[a]	12.321	24.437[a]	11.225	None
0.013	0.858	4.130	0.858	4.130	At most 1
Normalized cointegration equation: EL = 23.492 × GDP					

Notes: Trace and maximal eigenvalue tests indicate the existence of one cointegration equation at 5% level.
[a] Denotes rejection of the hypothesis at 5% level. The lag length has been chosen based on minimum AIC.

Table 6
Results of robustness tests and stability tests for electricity equation in the ECM.

	1980–2007		1990–2007	
	Value	Prob.	Value	Prob.
Panel A: Robustness tests				
LM(4) [$\chi^2(4)$]	3.8384	0.4283	1.3165	0.8586
RESET [$F(m,n)$]	0.0456	0.8253	0.4129	0.5229
BPG [χ^2 (5)]	6.5542	0.2560	5.9345	0.3126
ARCH [χ^2 (4)]	0.2924	0.5887	0.2549	0.6136
Jarque–Bera	1.2597	0.5327	0.8463	0.6550
Panel B: Stability tests				
Maximum LR *F*-statistic (1989q1)	3.3399	1.0000		
Maximum LR *F*-statistic (1998q4)			2.4912	1.000
Maximum Wald *F*-statistic	3.3399	1.0000	2.4912	1.000
Exp LR *F*-statistic	0.9567	1.0000	0.5052	1.000
Exp Wald *F*-statistic	0.9567	1.0000	0.5052	1.000
Ave LR *F*-statistic	1.6927	1.0000	0.9041	1.000
Ave Wald *F*-statistic	1.6927	1.0000	0.9041	1.000
Panel C: Chow forecast tests				
Forecast from 1989q1 to 2007q4	1.2888	0.2329		
Forecast from 1998q4 to 2007q4			0.9306	0.5865

relation indicates that the real GDP and EC have an inherent co-movement tendency over the long run.

Cointegration implies the existence of causality, at least in one direction. However, it does not indicate the direction of the causal relationship. Hence, to shed light on the direction of causality, the ECM based causality tests are performed. The short run *F*-statistics, long run *t*-statistics and joint *F*-statistics for Eq. (1) and (2) are reported in Table 5. The results show that only the electricity equation (Eq. (1)) contains the significant variables. However, no significant variable is contained in the GDP equation (Eq. (2)). Thus, the robustness of electricity equation is checked for two sample periods. Generally speaking, the equation appears to be robust to various departures from standard regression assumptions in terms of residual correlation by Lagrange multiplier (LM) test, heteroscedasticity by BPG test [47,48], autoregressive conditional heteroscedasticity by ARCH test [49], misspecification of functional form by RESET test [50], or non-normality of residuals by Jarque–Bera test. Panel A of Table 6 displays the results from these tests. For sample period 2, the Jarque–Bera test is performed by smoothing the outlier residual in 1998q3, which corresponds to the 921 earthquake (dated on September 21) in Taiwan.

Table 5 shows that short run causality is found only from real GDP to EL, but not the reverse, i.e., there is unidirectional Granger causality. The coefficients of ECT are found to be significant in the EC equation, which indicates that given any deviation in the ECT, both variables in the ECM would interact in a dynamic fashion to restore long run equilibrium. Moreover, the interactive term of

Table 5
Results of causality tests based on the ECM.

Dependent variables	Source of causation (independent variable)				
	Short run		Long run	Joint (short-run/ECT)	
	ΔLGDPSA	ΔLELSA	ECT_{t-1}	ΔLELSA, ECT_{t-1}	ΔLGDPSA, ECT_{t-1}
	F-statistics		*t*-statistics	*F*-statistics	
Panel A: sample period 1980–2007					
ΔLGDPSA		1.046	0.720	0.831	
ΔLELSA	3.489[a]		−3.606[a]		7.845[a]
Panel B: sample period 1990–2007					
ΔLGDPSA		0.092	−1.812	1.177	
ΔLELSA	4.299[a]		−2.448[a]		6.529[a]

The lag lengths are selected using Akaike's information criterion.
[a] Implies significance at the 5% level.

change in GDP (ΔGDP), along with the ECT in the electricity equation, is significant at 1% level. These indicate that GDP is strongly exogenous and whenever a shock occurs in the system, EC would make short run adjustments to restore long run equilibrium. Hence, bringing domestic electricity prices in line with international market prices or any well-designed conservation policy can play an effective role in managing the electricity sector.

3.3. Constancy of cointegration space

One important problem with ECMs is that the estimated parameters may change over time. Unstable parameters can result in model misspecification and, if any structural break exists, necessary adjustment of the ECM parameters and variables to reflect the structure break should be made [3]. Once the ECM has been estimated, the author assesses the parameter constancy by using the cumulative sum of recursive residuals (CUSUM) and the CUSUM of square (CUSUMSQ) tests, which were proposed by Brown et al. [51]. In this study, only the electricity equation contains a significant ECT, which can be derived from the long run cointegrating vector. Thus, the CUSUM and CUSUMSQ tests are needed

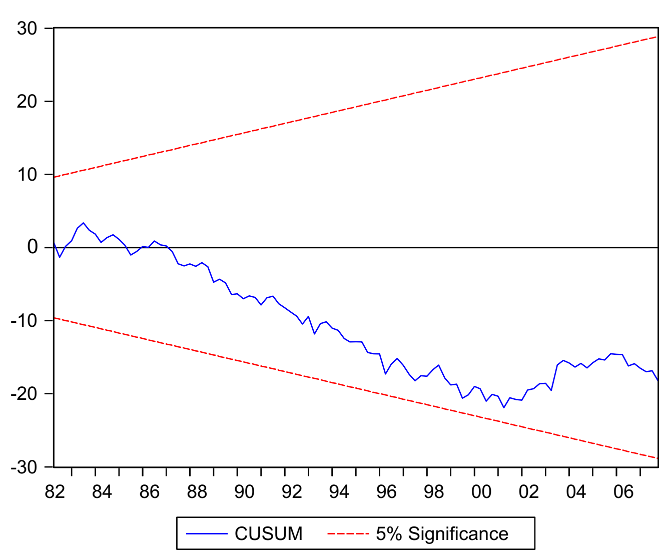

Fig. 3. Plot of the CUSUM for dependent variable LELSA, 1980–2007.

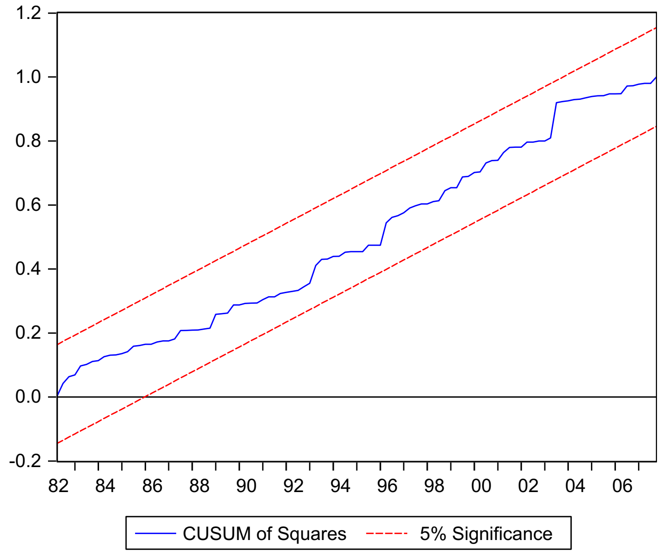

Fig. 4. Plot of the CUSUMSQ for dependent variable LELSA, 1980–2007.

only for the electricity equation [3]. The equation is estimated by OLS first and the residual is subjected to the CUSUM and CUSUMSQ tests. Figs. 3,4 plot the CUSUM and CUSUMSQ statistics when EC is the dependent variable. The results indicate no instability in the coefficients as the plots of the CUSUM and CUSUMSQ statistics are confined within the 5% critical bounds of parameter stability.

In addition, the plot of the recursive estimates of each coefficient from electricity equation is shown in Fig. 5 for sample period 1. If the coefficient estimation displays significant variation, as more data are added to estimate the electricity equation, it is a strong indication of instability of coefficient estimation. In Fig. 5, the estimated coefficients rise steadily as more data are added to the electricity equation.

Furthermore, the Quandt-Andrews unknown breakpoint tests [52] are also employed to test for unknown structural breakpoint amongst all the regressors from the electricity equation for two sample periods. The tests are performed with 10% of trimming on the data set. The results shown in panel B of Table 6 fail to reject the null hypothesis of no structure break. Since Eq. (1) is linear, the results of LR *F*-statistic are identical to the results of Wald *F*-statistic as shown in panel B of Table 6. The maximum *F*-statistics are in 1989q1 and 1998q4 for sample 1 and 2, respectively, and that are the most likely breakpoint locations. Therefore, the Chow's forecast tests are performed and specify 1989q1 and 1998q4 as the first observations in the forecast period for two sample periods, respectively. The tests reestimate the electricity equation for the periods 1980q1 to 1988q4 and 1990q1 to 1998q3 for two sample period, and use the result to compute the prediction errors for the remaining quarters. The results shown in panel C of Table 6 fail to reject the null hypothesis of no structure change in the electricity equation before and after 1989q1 for sample 1 and 1998q4 for sample 2, respectively.

Overall, the structure of the parameters has not diverged abnormally over the period from 1980 to 2007. It appears that applying Granger causality tests based on the ECM does not suffer from any problem caused by a structure change during the 1980–2007 period, and the coefficient estimates of ECM are stable. Thus,

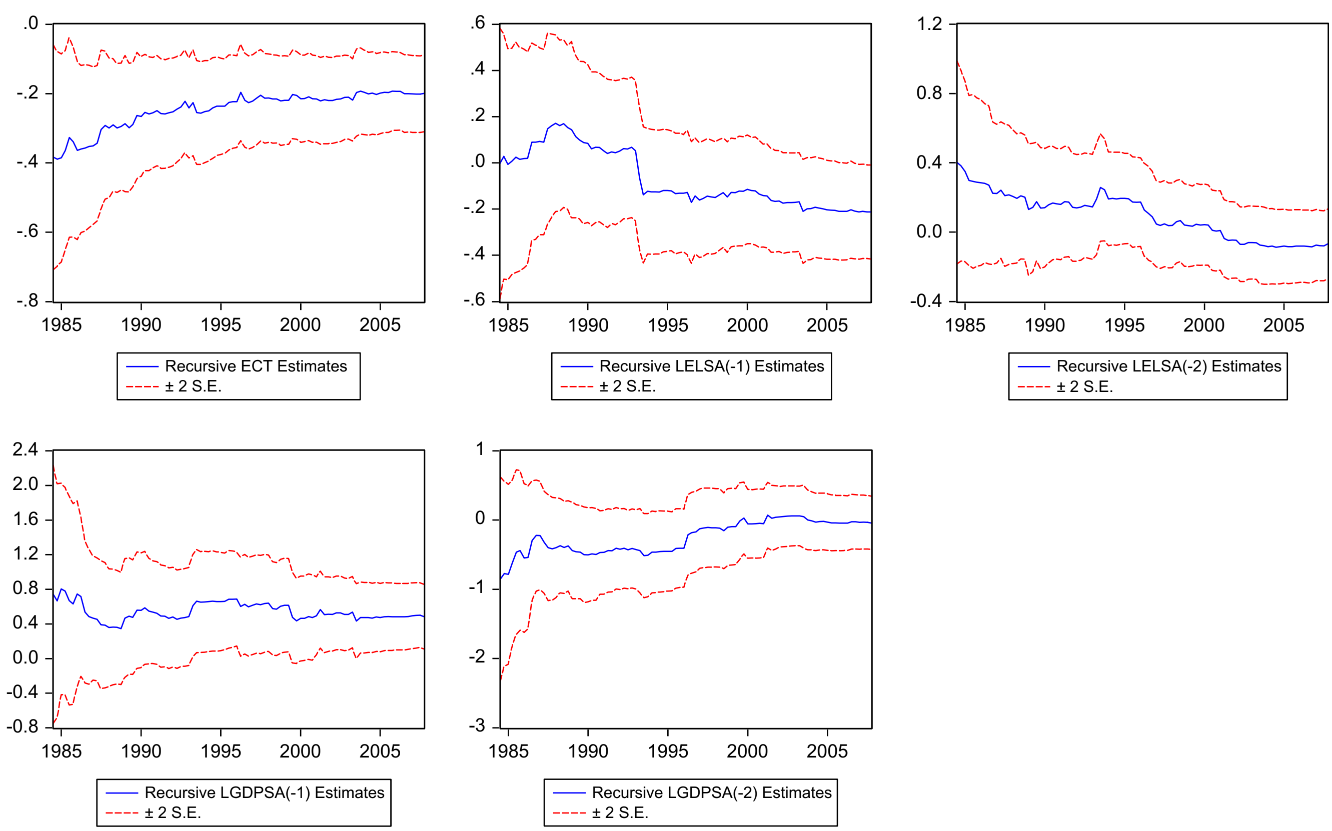

Fig. 5. Plot of the recursive coefficient estimates for electricity equation from, 1980 to 2007.

panel B in Tables 3–5 indicate that the results of stationarity, cointegration and causality relationship during 1990–2007 are similar to the results during 1980–2007. That is, there is unidirectional Granger causality running from GDP to EC in the long and short run, while electricity has a neutral effect on GDP in both the short and long run.

3.4. Building SARIMA models

The EC series given in Fig. 1 assumes that the seasonality and the trend exist in the historical data and extend to the future with the same pattern, thus the univariate SARIMA models are employed using sample period 2. According to the autocorrelation function (acf) and partial autocorrelation function (pacf) of EL, the first regular and first seasonal differences are employed to remove the growth trend and the seasonality characteristics. During this process, the first five observations are lost. The acquired stationary time series can be used to identify the SARIMA model. AIC is used to determine the best model. At the seasonal level, the acf has a spike at lag 4 and cuts off after lag 4 and the pacf dies down. At the nonseasonal level, the acf has a spike at lag 1 and cuts off after lag 1, and the pacf dies down. As we can see here, the best available model generated from the estimation data set is SARIMA $(0,1,1)\otimes(0,1,1)_4$. The residual analysis indicates that the model is adequate. The estimated model equation is as follows.

$$\left(1-B\right)\left(1-B^4\right)(\mathrm{EL}_t \text{ or GDP}) = \mu + (1-\theta_1 B)\left(1-\theta_2 B^4\right)a_t \tag{5}$$

In accordance with the process of building the EL model, the best available model for real GDP is obtained. It is the SARIMA $(0,1,1)\otimes(0,1,1)_4$ with no intercept model, as shown in Eq. (5). The residual analysis indicates that the GDP model is adequate. For both EL and real GDP variables, using 12-year, 13-year,…,17-year quarterly data sets and full data sets from 1990 to 2001, 1990 to 2002,…, 1990 to 2006 and 1990 to 2007 as estimation periods, the estimated coefficients on SARIMA models are shown in Table 6. The forecast values are shown in Figs. 6(a–c) and 7(a–c) for EL and GDP, respectively. The out-of-sample forecasting abilities of the SARIMA models are evaluated and compared with STSP and ECSTSP models by using testing data during the following periods: 2002–2007, 2003–2007,…, and 2007. Three statistics, root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), are used as performance criteria. Results are shown in Tables 7 and 8. The MAPE results are a means to judge the accuracy of the forecast, in which MAPE less than 10% is a highly accurate forecast [53]. For both EL and real GDP, the estimated SARIMA models using full data sets are employed to forecast over the period 2008–2015. Results are shown in Table A1, Figs. 6(d) and 7(d).

3.5. Building STSP and ECSTSP multivariate models

The SAS STATESPACE procedure is appropriate for jointly forecasting several related time series that are dynamically interacting. The procedure selects the STSP model automatically and assumes that the input series are stationary. If the series are nonstationary, then the process may fail. Based on the ADF and PP statistics, panel B of Table 3 shows that the integrations of EL and real GDP are $I(1)$, respectively. The result of the Johansen test in panel B of Table 4 indicates that both EL and GDP are cointegrated. Thus, the ECT derived from the long run cointegration relationship is stationary. Taking the cointegration relationship into account, the proposed ECSTSP model with vector $x_t = (\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t)$ is constructed. The classical STSP model with vector $x_t = (\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t)$ is also constructed, where the x_t vector is defined in Eq. (4). Even though the variables have been differenced for stationarity, STATESPACE procedure forecasts them in their non-differenced level. For both EL and GDP variables, using 12- ,13-,…, 17-year data sets and the full data sets in period 2, the seven state vectors: $\mathbf{z_{1t}}, \mathbf{z_{2t}},\ldots,\mathbf{z_{6t}}, \mathbf{z_{Full}}$ of ECSTSP models and the seven state vectors: $\mathbf{y_{1t}}, \mathbf{y_{2t}},\ldots,\mathbf{y_{6t}}, \mathbf{y_{Full}}$ of STSP models are expressed as follows:

$$\begin{aligned}
z_{1t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{GDP}_{t+2|t}\right)',\\
z_{2t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{GDP}_{t+2|t}\right)',\\
z_{3t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{GDP}_{t+2|t}\right)',\\
z_{4t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t, \Delta\mathrm{GDP}_{t+1|t}\right)',\\
z_{5t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}\right)'\\
z_{6t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \mathrm{ECT}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}\right)'\\
z_{\mathrm{Full}} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, ECT_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}\right)'
\end{aligned} \tag{6}$$

and

$$\begin{aligned}
y_{1t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{GDP}_{t+2|t}\right)',\\
y_{2t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{GDP}_{t+2|t}\right)',\\
y_{3t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}\right)',\\
y_{4t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}\right)',\\
y_{5t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}\right)'\\
y_{6t} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}\right)'\\
y_{\mathrm{Full}} &= \left(\Delta\mathrm{GDP}_t, \Delta\mathrm{EL}_t, \Delta\mathrm{GDP}_{t+1|t}, \Delta\mathrm{EL}_{t+1|t}, \Delta EL_{t+2|t}\right)'
\end{aligned} \tag{7}$$

The out-of-sample forecasting performances are shown in Table 7 by using testing data. The forecast values are shown in Figs. 5 (a–c) and 6 (a–c) for two variables.

Both $\mathrm{ECSTSP_{Full}}$ and $\mathrm{STSP_{Full}}$ models with $\mathbf{z_{Full}}$ and $\mathbf{y_{Full}}$ state vectors are used to predict EC and real GDP simultaneously over the period 2008–2015. Results are shown in Table A1, Figs. 5(d) and 6(d). The $\mathbf{z_{Full}}$ and $\mathbf{y_{Full}}$ state vectors corresponding to transition and input matrices $\mathbf{F_{Full}}$ and $\mathbf{G_{Full}}$; specified in Eq. (4), are presented in the following:

$$\begin{aligned}
z_{\mathrm{Full}} &= \begin{bmatrix} \Delta\mathrm{GDP}_t \\ \Delta\mathrm{EL}_t \\ \mathrm{ECT}_t \\ \Delta\mathrm{GDP}_{t+1|t} \\ \Delta\mathrm{EL}_{t+1|t} \end{bmatrix}\\
&= \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0.04 & -0.00 & 0.85^{*} & 0.92^{*} & -0.04^{*} \\ -0.19 & 0.00 & 0.03 & -0.36^{\#} & 0.01^{*} \\ 7.65 & -0.65^{*} & -0.19 & -28.41^{*} & 0.22^{\#} \end{bmatrix}\\
&\quad \times \begin{bmatrix} \Delta\mathrm{GDP}_{t-1} \\ \Delta\mathrm{EL}_{t-1} \\ \mathrm{ECT}_{t-1} \\ \Delta\mathrm{GDP}_{t|t-1} \\ \Delta\mathrm{EL}_{t|t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0.41^{*} & -0.02^{*} & -0.21^{\#} \\ -7.75 & 0.11 & 15.93^{*} \end{bmatrix} \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \end{bmatrix}
\end{aligned} \tag{8}$$

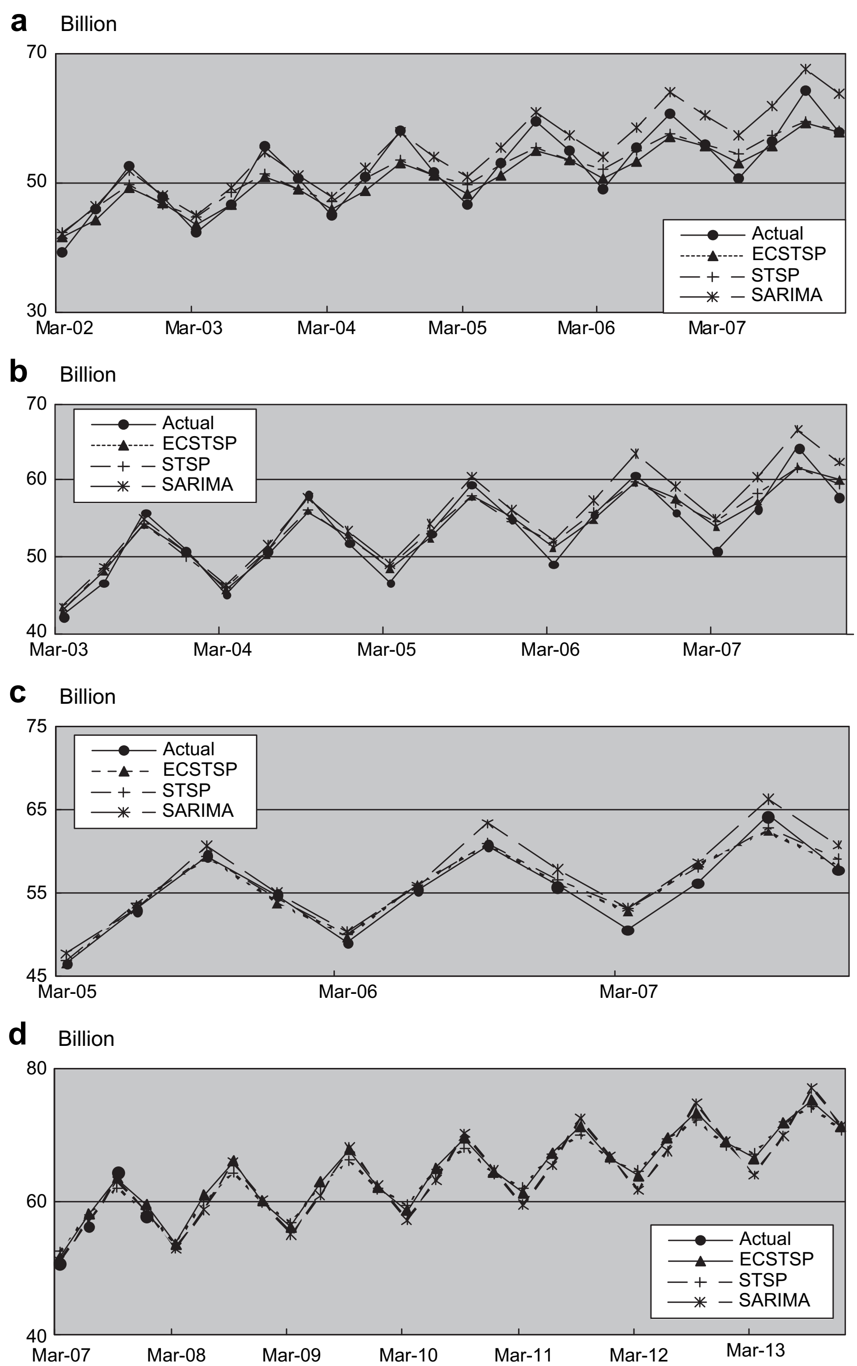

Fig. 6. Comparison of predicted electricity consumption using ECSTSP, STSP and SARIMA models.

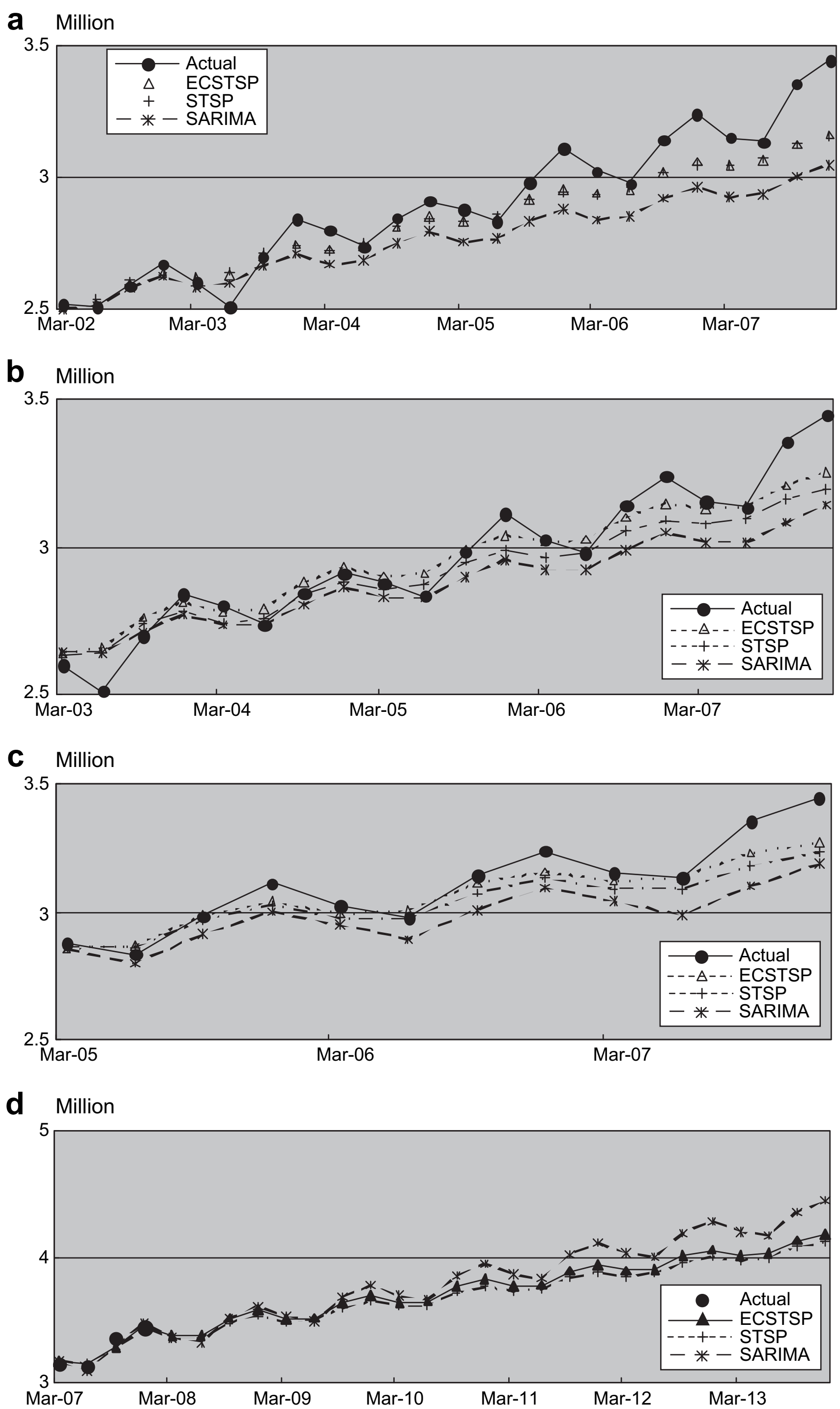

Fig. 7. Comparison of predicted real GDP using ECSTSP, STSP and SARIMA models.

Table 7
SARIMA coefficients for electricity consumption and real GDP in Taiwan.

Estimation period	Electricity consumption			Real GDP	
	θ_0	θ_1	θ_2	θ_1	θ_2
1990–2001	28,201.0[a]	0.8854[a]	0.6769[a]	−0.2709[b]	0.7991[a]
1990–2002	23,850.4[a]	0.8814[a]	0.5896[a]	−0.3189[a]	0.7036[a]
1990–2003	21,674.0[a]	0.9030[a]	0.4911[a]	−0.3381[a]	0.4697[a]
1990–2004	19,755.2[a]	0.8889[a]	0.5127[a]	−0.3400[a]	0.5192[a]
1990–2005	15,887.4	0.8476[a]	0.5169[a]	−0.3468[a]	0.5098[a]
1990–2006	8562.3	0.7616[a]	0.5093[a]	−0.3088[a]	0.5168[a]
1990–2007	7458.6	0.7584[a]	0.5196[a]	−0.3296[a]	0.4734[a]

[a] Denote significance at the 5% level.
[b] Denote significance at the 10% level.

$$y_{\mathrm{Full}} = \begin{bmatrix} \Delta\mathrm{GDP}_t \\ \Delta\mathrm{EL}_t \\ \Delta\mathrm{GDP}_{t+1|t} \\ \Delta\mathrm{EL}_{t+1|t} \\ \Delta\mathrm{EL}_{t+2|t} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ -0.10 & -0.00 & 0.04 & 0.01^{*} & 0 \\ 0 & 0 & 0 & 0 & 1 \\ -9.01^{\#} & -0.40^{\#} & 31.60^{*} & -1.21^{*} & -0.06 \end{bmatrix} \times \begin{bmatrix} \Delta\mathrm{GDP}_{t-1} \\ \Delta\mathrm{EL}_{t-1} \\ \Delta\mathrm{GDP}_{t|t-1} \\ \Delta\mathrm{EL}_{t|t-1} \\ \Delta\mathrm{EL}_{t+1|t-1} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0.12 & -0.00 \\ -4.21 & -0.55^{*} \\ 10.73^{*} & -0.77^{*} \end{bmatrix} \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix} \tag{9}$$

The * and $^{\#}$ on the coefficients of the transition and input matrices F and G indicate that they are significant at the 5% and 10% level, respectively.

3.6. Out-of-sample forecasting performance comparisons

The forecasting ability of the new multivariate ECSTSP model is compared with the multivariate ECSTSP and univariate SARIMA models. In general, the forecasting performance of the multivariate models is highly dependent on the availability and reliability of data on independent variables over the forecasting period, which requires further efforts in data collection and estimation. On the other hand, univariate time series analysis provides another modeling approach, which only requires the historical data of the variable of interest to forecast its future evolution behavior. Therefore, the prediction error of univariate model can be less than the prediction error of multivariate model. However, if the multivariate model has stronger modeling power than the associated univariate model, the multivariate model is likely to achieve better prediction performance. For the performance evaluation, the predictive accuracies of the three models for both EC and real GDP are compared over the six different forecast horizons, 6-year, 5-year,..., 1-year, using sample period 2. Four observations can be made. First, all of the models have strong forecasting performance, because all of the MAPEs are less than 5.4%. Second, the ECSTSPs have the smallest average values of MAPEs over six forecasting horizons for both EL and GDP, which are 2.50% and 1.74%, respectively. For two variables, the average values of MAPEs are $\mathrm{MAPE}_{\mathrm{ECSTSP}} < \mathrm{MAPE}_{\mathrm{STSP}} < \mathrm{MAPE}_{\mathrm{SARIMA}}$ (shown in Table 7). Third, the forecasting accuracies of both ECSTSP and STSP are not sensitive to the length of forecast horizon, but the forecasting accuracies of SARIMA models are. For two variables, the variances of MAPEs (VMAPE) over six forecasting horizons are $\mathrm{VMAPE}_{\mathrm{STSP}} < \mathrm{VMAPE}_{\mathrm{ECSTSP}} < \mathrm{VMAPE}_{\mathrm{SARIMA}}$ (shown in Table 7). For short-term prediction (1 and 2 year), the univariate SARIMA models are as good as ECSTSP ones for both series. These results may be expected since the SARIMA model is available for short prediction periods. For long-term prediction periods (3-year to 6-year), both STSP and ECSTSP models are better than SARIMA models, because the STSP model is appropriate for jointly forecasting several related time series that dynamically interact. Finally, for long-term prediction, the best models are ECSTSP for two variables, because the cointegration relationship between real GDP and EC is taken into account in the ECSTSP model.

This study concludes by using three models to forecast both EC and real GDP for Taiwan up to year 2013. The forecasts of two variables over the 2008–2013 period, together with the actual data

Table 8
Out-of-sample comparisons between ECSTSP, STSP and SARIMA models.

	ECSTSP		STSP		SARIMA	
	Electricity	GDP	Electricity	GDP	Electricity	GDP
Forecasting period 2002–2007						
RMSE	2,580,842.88	106,427.89	2,601,980.83	110,754.40	3,311,868.93	172,511.25
MAE	2,080,817.21	77,478.10	2,100,604.05	82,061.58	2,754,532.04	137,231.42
MAPE	3.90%	2.53%	4.04%	2.69%	5.32%	4.47%
Forecasting period 2003–2007						
RMSE	1,596,771.96	76,284.54	1,693,889.88	96,808.67	2,384,135.37	130,307.88
MAE	1,373,947.66	56,878.51	1,393,269.02	72,323.68	2,022,144.92	102,174.30
MAPE	2.57%	1.90%	2.62%	2.36%	3.79%	3.31%
Forecasting period 2004–2007						
RMSE	1,645,895.44	41,111.90	1,684,145.67	68,269.16	2,053,217.94	66,971.61
MAE	1,278,933.98	33,567.65	1,300,411.04	51,318.58	1,660,985.40	49,728.90
MAPE	2.38%	1.10%	2.43%	1.65%	3.01%	1.60%
Forecasting period 2005–2007						
RMSE	1,136,792.72	72,618.97	1,159,622.34	95,316.45	1,855,532.67	140,591.78
MAE	842,647.20	52,837.55	957,385.07	72,117.83	1,594,815.12	121,331.24
MAPE	1.52%	1.64%	1.75%	2.23%	2.87%	3.80%
Forecasting period 2006–2007						
RMSE	1,561,909.54	64,567.62	1,423,396.02	62,189.97	1,404,183.40	50,346.40
MAE	1,419,260.35	47,838.60	1,291,615.37	47,653.14	1,229,182.90	45,842.32
MAPE	2.57%	1.46%	2.34%	1.46%	2.18%	1.46%
Forecasting period 2007						
RMSE	1,329,412.62	71,722.45	1,525,655.64	70,404.47	731,592.56	58,937.36
MAE	1,148,128.67	59,992.16	1,347,123.71	61,411.96	694,850.52	48,567.61
MAPE	2.04%	1.79%	2.39%	1.84%	1.20%	1.45%
Mean (MAPE)	2.50%	1.74%	2.60%	2.04%	3.06%	2.68%
Var (MAPE)	0.53	0.19	0.50	0.18	1.65	1.50

in 2007, are illustrated in Figs. 6(d) and 7(d) and presented in detail in Appendix A. Table A1, Figs. 6(d) and 7(d) show that the forecasted values of ECSTSP are less than SARIMA and greater than STSP, especially in the second half of the forecasting period. Thus, the ECSTST model tends to give values that are neither too large nor too small for long-term forecast among the three different models.

4. Discussion and policy implications

The finding of unilateral short and long run causality from real GDP to EC without any feedback effects can be explained from a perspective of economic structure and electricity usage structure. In many Asian developing countries, economic growth is causing the industrial and commercial sectors, where electricity has been used as a basic energy input, to expand [5]. In Taiwan, the annual average growth rates of EC of the industrial, commercial and household sectors are 6.05% 7.52% and 5.85% respectively, with the annual average growth rate of real GDP about 5.4% from 1990 to 2007. Hence, the expansion in GDP also increases the need for electricity. Economic growth results in a higher proportion of national income to spend on highly electricity-consuming goods and/or services such as plasma display panel televisions and high-speed wired or wireless Internet connections, and thereby stimulates further EC. Intuitively, increased real income requires enormous EC.

Moreover, the empirical results indicate that there is no causality running from EC to economic growth. In Taiwan, the energy intensity (defined as the amount of energy consumed per GDP) is 8532 Btu/USD in 2007, which is more than the average energy intensity in Asia and Oceania (6706 Btu/USD), and is also more than the average energy intensity in the world (8035 Btu/USD) (Energy Information Administrator (EIA), 2007). The higher energy intensity in Taiwan reflects inefficient energy usage in industry, as well as in the commercial and household sectors. This indicates that much improvement needs to be made in EC efficiency. Hence, electricity efficiency and conservation will not hurt economic growth and development.

The results of this paper suggest that electricity conservation policies such as rationalizing the tariff structure, improving efficiency and managing demand, which aim at curtailing waste of electricity and reducing EC without affecting the end-use benefits, can be adopted because they bring no harm to Taiwan's economic growth. Moreover, around 57% of electricity was consumed for industrial production in 2007. Therefore, the government of Taiwan should also encourage domestic industries to adopt new technologies to minimize CO_2 emissions in order to respond to the recommendations of the Kyoto protocol.

5. Conclusions

This paper examines the causality between EC and real GDP in Taiwan during 1980–2007 using the ECM model for seasonally adjusted quarterly data. The sub-period from 1990 to 2007 is employed to confirm parameter stability in estimating the ECM. The results indicate the following: (1) both series appear to be nonstationary in levels, but stationary in the first differences for actual value and logarithmic form; (2) a stationary linear cointegration relationship between two variables exists; (3) there is unidirectional short and long run strong Granger causality from economic growth to EC, while electricity has a neutral effect on GDP in both the short and long run; and (4) no structure change exists during 1980–2007 and the estimated parameters of ECM are stable. Therefore, energy conservation is a feasible policy with no damaging repercussions on economic growth for Taiwan.

The finding of this paper is compared with three of the leading research results [5,11,17]. In [5], Chen et al. found that electricity and GDP are neutral with respect to each other in 31 annual observations over the period 1971 to 2001. Lee and Chang [11] found that a unidirectional causality runs from EC to economic growth based on the 50 annual observations during 1954–2003. Yang [17] found that a bidirectional causal linkages between GDP and EC from the 44 annual observations during 1954–1997. The difference in the findings or the results of this study and that of [5,11,17] may largely be attributed to the choice of the sample periods and the sampling data sets. The sample periods used in this paper are 1980–2007 and 1990–2007. And, the sampling data used in articles [5,11,17] are 31, 50, and 44 annual data sets respectively. While, this study adopts seasonally adjusted data sets, e.g., 112 and 72 quarterly data sets for two sample periods, respectively.

Furthermore, due to the rapid growth in both economy and EC in Taiwan, forecasting both variables is of the utmost significance to the reconstruction process going on in Taiwan, especially to that of the energy generation systems. Thus, this study proposes a new ECSTSP model to forecast both EL and real GDP simultaneously, taking the cointegration relationship into account. The out-of-sample forecasting ability of the ECSTSP model is to be compared with both STSP and SARIMA multivariate and univariate benchmark models over six forecast horizons. The investigation results suggest that all of the models have strong forecasting performance with MAPE less than 5.4%, but the ECSTSPs have the smallest average values of MAPEs over six forecasting horizons for both EL and GDP, which are 2.50% and 1.74%, respectively, while the average values of MAPE for SARIMA are 3.06% and 2.68%. Both STSP and ECSTSP models have smaller variance of MAPEs over six forecasting horizons than SARIMA models. These results indicate that the forecasting accuracies of STSP models are not sensitive to the length of forecast horizon, but SARIMA models are. For short-term prediction, the univariate SARIMA models are as good as ECSTSP ones for both series. These results may be expected since the SARIMA model is available for short prediction periods. For long-term prediction, both STSP and ECSTSP models are better than SARIMA models, because the STSP model is appropriate for jointly forecasting several related time series that dynamically interact. For long-term prediction, the best models are ECSTSP for two variables, because the cointegration relationship between real GDP and EC is taken into account in this method.

In the future, it will be possible to explore the causality relationship between industrial sector EC and other economic factors, e.g., employment or income, and to forecast EC in Taiwan using multivariate linear or nonlinear models.

Acknowledgments

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Appendix A. Electricity consumption and real GDP forecast results during 2007–2013

The forecasts of two variables over the 2008–2013 periods, together with the actual data in 2007, are presented in detail in Table A1. It shows that the ECSTST model tends to give values that are neither too large nor too small for long-term forecast among the three different models.

Table A1
Forecasts for electricity consumption and real GDP for Taiwan, 2007–2013.

Electricity consumption (kwh)					Real GDP			
Date	Actual	ECSTSP	STSP	SARIMA	Actual	ECSTSP	STSP	SARIMA
Mar-2007	50,701,637	51,663,499	52,488,618	51,090,844	3,152,427	3,168,121	3,177,247	3,168,466
Jun-2007	56,315,383	58,113,668	58,101,558	57,121,193	3,135,149	3,148,132	3,153,063	3,098,508
Sep-2007	64,305,493	63,457,851	62,091,182	63,098,841	3,358,002	3,284,883	3,275,344	3,296,605
Dec-2007	57,873,290	59,501,202	58,365,758	58,419,147	3,446,720	3,444,997	3,437,911	3,481,292
Mar-2008		53,720,909	53,761,967	52,956,674		3,380,523	3,361,709	3,358,718
Jun-2008		60,905,753	59,879,718	58,843,202		3,379,799	3,358,989	3,326,597
Sep-2008		66,087,459	64,364,457	65,896,274		3,517,143	3,478,496	3,514,669
Dec-2008		60,113,690	59,819,927	60,230,636		3,578,985	3,535,885	3,610,174
Mar-2009		56,167,044	56,887,821	55,106,383		3,510,861	3,487,286	3,527,566
Jun-2009		62,965,585	62,362,795	61,000,369		3,516,151	3,494,367	3,495,445
Sep-2009		67,757,661	66,145,193	68,060,900		3,644,962	3,598,897	3,683,517
Dec-2009		62,245,092	61,936,993	62,402,721		3,702,079	3,649,687	3,779,022
Mar-2010		58,729,371	59,526,853	57,285,926		3,640,588	3,608,794	3,696,414
Jun-2010		65,110,064	64,766,702	63,187,371		3,648,319	3,621,145	3,664,292
Sep-2010		69,521,095	68,101,977	70,255,360		3,769,301	3,720,470	3,852,365
Dec-2010		64,440,719	64,096,745	64,604,639		3,822,853	3,766,625	3,947,870
Mar-2011		61,312,826	62,096,062	59,495,303		3,767,750	3,730,061	3,865,261
Jun-2011		67,297,363	67,142,102	65,404,207		3,777,856	3,746,671	3,833,140
Sep-2011		71,356,982	70,092,276	72,479,654		3,891,798	3,841,991	4,021,212
Dec-2011		66,675,933	66,279,145	66,836,392		3,942,324	3,884,165	4,116,718
Mar-2012		63,898,043	64,644,191	61,734,514		3,893,310	3,851,468	4,034,109
Jun-2012		69,509,822	69,497,618	67,650,877		3,905,678	3,871,823	4,001,988
Sep-2012		73,246,732	72,099,360	74,733,783		4,013,219	3,963,352	4,190,060
Dec-2012		68,935,762	68,479,825	69,097,979		4,061,134	4,001,997	4,285,566
Mar-2013		66,474,656	67,177,063	64,003,560		4,017,867	3,973,034	4,202,957
Jun-2013		71,736,846	71,836,013	69,927,381		4,032,342	3,996,714	4,170,836
Sep-2013		75,178,310	74,121,107	77,017,746		4,134,023	4,084,562	4,358,908
Dec-2013		71,211,018	70,696,651	71,389,401		4,179,661	4,120,077	4,454,414

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