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The causal relationship between electricity consumption and economic growth in a Gaming and Tourism Center: The case of Macao SAR, the People's Republic of China

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A R T I C L E   I N F O

Article history:
Received 4 August 2009
Accepted 25 November 2010
Available online 31 December 2010

Keywords:
Electricity consumption
Economic growth
Vector error correction model

A B S T R A C T

A number of Asian cities decided to establish gaming and resort facilities in order to capitalize on the growing number of gamblers and their family members in Asia. In doing so, they expect to sustain economic growth but, on the other hand, will consume a considerable amount of energy. Nevertheless, the causal relationship between economic growth and electricity consumption in this type of service-oriented territories has never been investigated. Using the historical data obtained from the Government of Macao SAR, we found that electricity consumption and economic growth in terms of gross domestic product are co-integrated for the period of 1999 Quarter 1–2008 Quarter 4. Moreover, vector error correction (VEC) models indicated a lack of short-run relationships but showed that there was a long-run equilibrium relationship between electricity consumption and gross domestic product. The accuracy of VEC models was assessed by using the mean squared error and the mean absolute error. The error analysis shows that VEC models reproduced time series of gross domestic product and electricity consumption in difference form accurately.

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1. Introduction

Macao, a special administrative region in the People's Republic of China, has experienced a phenomenal economic growth since the liberalization of the gaming industry in 2002. According to the statistics provided by the Gaming Inspection and Coordination Bureau of Macao, gross revenue from Macao's casinos amounted to US$13.6 billion in 2008, representing an increase of 31% on year-to-year basis [1]. This figure exceeded the gross income of US$6.12 billion from Las Vegas Strip's casinos as reported by the Nevada Gaming Commission by a very wide margin. The direct taxes from gaming amounted to US$4.9 billion in 2008, representing 77% of the total income of the Government of Macao SAR. Besides, the annualized gross domestic product (GDP) per capita in Macao was estimated as US$39,036 at the end of 2008, higher than that of Hong Kong and Singapore. As the majority of Macao GDP (62.25%) depends on the gaming and the associated hospitality services provided to visitors, the change in GDP is a good proxy for economic growth in Macao – the world gaming center. In fact, many Asian cities including Singapore and Penghu of Taiwan have decided or proposed to jump on the bandwagon. However, this type of service industry, like the manufacturing sector, consumes a substantial amount of electricity to operate and brighten its infrastructure such as casinos, hotels, resorts, and meeting, exhibition and convention venues day and night. To cope with the increasing demand of electricity consumption, public policy makers in those cities need to have a better understanding on the relationships between economic activities, electricity consumption, and economic growth.

The purposes of this paper are, therefore, (i) to describe the relationship between economic activities and electricity consumption, and (ii) to investigate the long-run relationship and short-run causality relationship between electricity consumption and economic growth in terms of GDP in Macao. The paper is organized as follows. In the next section, we review previous studies on modeling of electricity consumption and literature on causality studies of energy consumption and economic growth.
In Section 3, the methodology adopted in the study is presented. Section 4 describes the data employed and reports the findings. Concluding remarks and policy implications are given in Section 5.

2. Literature review on modeling of electricity consumption and the causal relationship between energy consumption and economic growth

Numerous studies have been conducted to examine the relationship between electricity consumption and various economic indicators in the past fifty years. In the 1950s, Houthakker [2] analyzed electricity demand on domestic two-part tariffs for 42 provincial towns in the U.K. He found that average annual electricity consumption per consumer was a function of the average income per household, marginal price of elasticity and marginal price of competing forms of energy, such as gas. Houthakker also reported that the monthly electricity consumption of families had a strong seasonal variation, depending on average temperature and average hours of daylight per day for each month. Foss [3] studied the utilization of capital equipment and suggested that electricity consumption was an indicator of capital usage, especially in an industrial country such as the USA. Foss’s idea was adopted by Jorgensen and Griliches [4] and Heathfield [5] to measure capital usage using electricity consumption data. Mount et al. [6] analyzed both the short-run and long-run demand for electricity for three classes of consumers, namely residential, commercial and industrial. They demonstrated that long-run electricity demand was generally price elastic and became increasingly elastic as prices rose. In contrast, demand was general inelastic with respect to income, especially for residential and industrial classes that approached zero as income increased. Population exhibited approximately unit elasticity for all classes implying the common practice of estimating demand models on a per capita basis to be reasonable. In the past decade, researchers [7–12] studied the modeling of electricity consumption in different countries or cities. When annual data were used, researchers [8,10] found that gross national product (GNP) or its derivative such as the number of tourists in a tourist center was the major determinant of electricity consumption. When monthly data were used, researchers found that population (POP), temperature (TEMP) and other economic or industrial factors are the major determinants of electricity consumption [7,9,11,12]. Moreover, Pao [11] reported that economic indicators such as gross domestic product (GDP) and consumer price index (CPI) have a very weak instantaneous effect on Taiwan’s electricity consumption. Lai et al. [12] used multiple regression, artificial neural work (ANN), and wavelet-ANN to model electricity consumption in Macao for the period of January 2000–December 2006. The results show that the total monthly electricity consumption depends on economic factors such as the number of visitors and their hotel-room occupancy rate, demographic and climatic conditions in Macao. Most of the more recent studies show electricity consumption to be strongly associated with the business activities of a country or city.

In pioneering the study of causal relationship between energy consumption and economic growth, Kraft and Kraft [13] used annual data on gross energy inputs and GNP between 1947 and 1974 in the USA and utilized the test for unidirectional causality as outlined by Sims [14]. They found the evidence of a unidirectional causality running from GNP to energy consumption. Yu and Hwang [15] reexamined the causality between energy consumption and GNP over the time period of 1947–1979 using annual data. However, they did not find any evidence to support any causality between energy consumption and GNP over the entire sample period. When the time period was changed to 1973–1981 and quarterly data were used, Yu and Hwang [15] reported that unidirectional causality ran from GNP to energy consumption. A year later, Yu and Choi [16] studied the causal relationship between energy consumption and GNP using Sims and Granger causality tests for five countries. They reported that there was (i) no causal relationship between energy consumption and GNP in the USA, UK and Poland; (ii) unidirectional causality from GNP to energy consumption in South Korea; and (iii) unidirectional causality from energy consumption to GNP in the Philippines. Nachane et al. [17] used Engle–Granger co-integration approach [18] to test the energy–GNP causality over the time period 1950–51 to 1984–85 for 16 countries. They reported that there was long-run relationship between energy consumption and GDP for 11 developing countries and 5 developed countries. Since then, many researchers [19–34] adopted Engle–Granger co-integration approach or its modified version to study the causal relationship between energy consumption or electricity consumption and economic growth such as GDP or GNP. Table 1 summarizes the empirical findings of the causality tests between energy consumption and economic growth over the past three decades. The results from more recent studies [23–34] showed that there was in general a relationship between energy consumption and economic growth. More specifically, Chontanawat et al. [32] suggested that causality from energy to GDP was found to be more prevalent in the Organization for Economic Cooperation and Development (OECD) countries compared to the developing non-OECD countries. However, when it comes to whether the increase in energy consumption is a result of or a cause of economic growth, there is no conclusive agreement on this issue, possibly due to other exogenous factors that may affect energy consumption and GDP simultaneously or sequentially (but have been ignored in most prior studies). Therefore, our study was aimed at studying the relationship between electricity consumption and GDP with the number of tourists and population as important exogenous factors in the world’s gaming center – Macao SAR using Johansen’s methodology [35].

3. Methodology

3.1. Granger causality

In his 1969 classic paper on causality, Granger [36] stated that a causal model with two variables is expressed as:

\[ X_t + b_0 Y_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \epsilon_t \]  

(1)

\[ Y_t + c_0 X_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \epsilon_t \]  

(2)

where \( X_t \) and \( Y_t \) are stationary time series. He mentioned that when \( b_0 = c_0 = 0 \), Eqs. (1) and (2) are the expression for a simple causal model. Granger further noticed that

"Whether or not a model involving some group of economic variables can be a simple causal model depends on what one considers to be the speed with which information flows through the economy and also on the sampling period of the data used. It might be true that when quarterly data are used (let alone the annual data), for example, a simple causal model is not sufficient to explain the relationships between the variables, while for monthly data a simple causal model would be all that is required. Thus, some nonsimple causal models may be constructed not because of the basic properties of the economy being studied but because of the data being used. It has been shown elsewhere that a simple causal mechanism can appear to be a feedback mechanism if the sampling period for the data is so long that details of causality cannot be picked out.” (Granger, 1969, p. 427)
Table 1

| Authors (Year) | Country | Time period | Methodologies | Findings |
|----------------|---------|-------------|----------------|----------|
| Kraft and Kraft (1978) [13] | USA | 1947–1974 annual data | Sims’ approach | GNP → energy consumption |
| Yu and Hwang (1984) [15] | USA | i. 1947–1979 annual data, ii. 1973–1981 quarterly data | Sims’ approach | GNP | energy consumption, GNP → energy consumption |
| Yu and Choi (1985) [16] | USA | 1963–1976 annual data | Sims and Granger causality tests | GNP | energy consumption, GNP → energy consumption |
| Nachane et al. (1988) [17] | 16 countries | 1951–1985 annual data | Co-integration and Granger causality tests | Exergy (the amount of energy available for useful work) was used in Warr and Ayres (2000) [23] for Taiwan, 1954–2000. |
| Cheng (1995) [19] | USA | 1947–1990 annual data | Hsiao’s version of the Granger causality | GNP | energy consumption |
| Masih and Masih (1996) [20] | India | 1955–1990 | Johansen’s multivariate co-integration tests | GNP | energy consumption |
| | Pakistan | 1955–1990 | | GNP → energy consumption |
| | Malaysia | 1960–1990 | | GNP | energy consumption |
| | Singapore | 1955–1990 | | GNP | energy consumption |
| | Indonesia | 1960–1990 | | GNP | energy consumption |
| | Philippines | 1955–1991 annual data | | GNP | energy consumption |
| Cheng and Lai (1997) [21] | Taiwan | 1955–1993 annual data | Co-integration and Hsiao’s version of the Granger causality tests | GDP | energy consumption |
| Glasure and Lee (1998) [22] | South Korea | 1961–1990 | Co-integration and Granger causality tests | GDP | energy consumption |
| | Singapore | 1961–1990 annual data | | GDP → energy consumption |
| Yang (2000) [23] | Taiwan | 1954–1997 annual data | Granger causality tests, Johansen’s method and vector error correction model | GDP | energy consumption |
| Houndroyannis et al. (2002) [24] | Greece | 1960–1996 annual data | Johansen’s method and vector error correction model | GDP | energy consumption |
| Ghosh (2002) [25] | India | 1951–1997 annual data | Co-integration and vector autoregression | GDP | electricity consumption |
| Shiu and Lam (2004) [26] | China | 1971–2000 annual data | Error correction model | GDP | electricity consumption |
| Oh and Lee (2004) [27] | South Korea | 1981–2000 quarterly data | Vector error correction model | GDP | energy consumption |
| Wolde-Rufael (2006) [28] | 17 African countries | 1971–2001 annual data | Toda-Yamamoto approach | Electricity consumption in Algeria, Congo Rep., Kenya, South Africa, and Sudan GDP → energy consumption |
| Yoo (2006) [29] | Indonesia | 1971–2002 annual data | Co-integration and Hsiao’s version of the Granger causality tests | GNP | energy consumption |
| | Malaysia | 1971–2002 annual data | | GDP → energy consumption |
| | Singapore | 1971–2002 annual data | | GDP → energy consumption |
| | Thailand | 1971–2002 annual data | | GDP → energy consumption |
| Yuan et al. (2007) [30] | China | 1978–2004 annual data | Error correction model | Real GDP | electricity consumption |
| Lee and Chang (2007) [31] | 22 developed countries & 18 developing countries | 1965–2002 | Panel VAR tests | GDP → energy consumption |
| | 18 developing countries | 1971–2002 annual data | | GDP → energy consumption |
| Chontanawata et al. (2008) [32] | 30 OECD countries and 78 non-OECD countries | 1960–2000 | Co-integration and Hsiao’s version of the Granger causality tests | 26 (87%) OECD countries display some form of Granger causality between energy and GDP, 51 (65%) non-OECD countries display some form of Granger-causality between energy and GDP. |
| | 1971–2000 annual data | | | |
| Pao (2009) [33] | Taiwan | 1980–2007 quarterly data | Error correction state space model | Real GDP → electricity consumption, Exergy → GDP |
| Warr and Ayres (2010) [34] | United States | 1946–2000 annual data | Co-integration and the Granger causality tests | | |

Note: ←, →, ↔ and [] mean “forward causality”, “backward causality”, “bidirectional causality” and “no relationship”, respectively.

* Exergy (the amount of energy available for useful work) was used in Warr and Ayres’s study [34].

Table 1 shows that there were relative few studies on the causal relationship between energy consumption and economic growth employed quarterly data and most of previous studies were all based on annual data. As the increase in GDP and electricity consumption is more pronounced only after Macao was returned to mainland China in 1999, our study decided to use quarterly data because of the number of data points available and its better ability to capture short-term changes.
3.2. Stationarity and co-integration

Standard Granger causality tests have to be conducted on stationary time series. Engle and Granger [18] stated that economic variables themselves may not be stationary and can have infinite variance, however, they can achieve temporarly stationary after differencing d times (where d is 1, 2, ... and so on) and the series can be designated as I(d). When two economic variables X_t and Y_t are both I(d), it is generally true that the linear combination \( Z_t = X_t - a_0 Y_t \) will also be I(d) (or I(d - b), b > 0). When the latter case occurs, a very special constraint operates on the long-run components of the series. And X_t and Y_t are called co-integrated. Following this line, we first test the unit roots of X_t and Y_t to confirm the stationary properties of each variable. This is achieved by using the Augmented Dickey–Fuller [37] test and the Phillips–Perron [38] test. For the time series X_t, the Augmented Dickey–Fuller (ADF) relationship is expressed as:

\[
\Delta X_t = \alpha + (\rho - 1)X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} + \epsilon_t
\]

where \( \Delta \) is the difference operator, \( p \) is the auto-regressive lag length that has to be large enough to eliminate possible serial correlation in \( \beta \) and \( \alpha \) (\( \rho \) and \( \rho \) are the coefficients of interest. For time series with strong seasonality, such as quarterly GDP, electricity consumption and the number of tourists, we apply seasonal adjustment before taking the logarithmic transformation as suggested by Pao [33].

When these variables are found to be non-stationary, we take the first-difference and then apply the ADF and Phillips–Perron tests again on the differenced data and so on. To test for co-integration, we employ the Johansen’s vector auto-regressive methodology [35].

3.3. Johansen’s vector auto-regressive (VAR) procedure

Intuitively, the Johansen’s VAR procedure is a multivariate version of the univariate Dickey–Fuller test. Considering a structural form VAR of order \( p \), we have

\[
A_0 Z_t = c_0 + \sum_{i=1}^{k} A_i Z_{t-i} + \epsilon_t, \quad t = 1, 2, ..., T
\]

where \( k \) is the number of lags, \( Z_{t}, Z_{t-1}, ..., Z_{t-k} \) are \((2 \times 1)\) vectors containing the logarithmic of seasonally adjusted GDP–ELEC pairs, \( A_0 \) is an \((2 \times 2)\) structural coefficient matrix, \( A_1, A_2, ..., A_k \) are \((2 \times 2)\) lag coefficient matrices, \( c_0 \) is an \((2 \times 1)\) vector containing constant terms, \( \epsilon_t \) is an \((2 \times 1)\) vector of disturbance terms. We can rewrite this structural VAR in error form (Verbeek [39], p. 326) as:

\[
A_0 \Delta Z_t = c_0 + \Pi Z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + \epsilon_t
\]

where \( \Pi = \sum_{i=1}^{n} A_i - A_0 \), \( \Gamma_i = -\sum_{j=1}^{i-1} A_j \), \( i = 1, 2, ..., k - 1 \). The \( \Pi \) matrix represents the adjustment to disequilibrium following an exogenous disturbance. If \( \Pi \) has a reduced rank \( r < k \) where \( r \) and \( k \) denote the rank of \( \Pi \) and the number of variables constituting the long-run relationship respectively, then there exist two \( k \times r \) matrices \( \alpha \) and \( \beta \), each with rank \( r \), such that \( \Pi = \alpha \beta^T \) and \( \beta \gamma \) is stationary. \( r \) is called the co-integration rank and each column of \( \beta \) is a co-integrating vector. Johansen’s VAR method estimates the \( \Pi \) matrix from an unrestricted VAR and tests whether one can reject the restrictions implied by the reduced rank of \( \Pi \).

There are two common approaches to test the reduced rank of \( \Pi \), namely the maximum eigenvalue test and the trace test. For the maximum eigenvalue test, the likelihood ratio is determined from:

\[
\text{LR}_{\max}(r+1) = -T \ln(1 - \lambda_{r+1})
\]

where \( T \) is the maximum time in the time series \( t \). The null hypothesis of \( r \) co-integrating vectors is tested against the alternative hypothesis of \( r + 1 \) or more co-integrating vectors. Since the co-integration tests are sensitive to the choice of lag length, we use the Schwartz Information Criteria to determine the optimal lag lengths. On the other hand, the likelihood ratio statistic for the trace test is:

\[
\text{LR}_{\text{trace}}(r|k) = -T \sum_{i=r+1}^{k} \ln(1 - \hat{\lambda}_i)
\]

where \( \hat{\lambda}_i \) is the estimated \( 2 - r \) smallest values and \( r = 0 \) and \( 1 \). The null hypothesis is that there are at most \( r \) co-integrating vectors. The alternative is that there are \( r \) or more co-integrating vectors. Again, we use the Schwartz Information Criteria to determine the optimal lag lengths.

3.4. Vector error correction (VEC) model

If two variables are co-integrated, there is causality between these two variables in at least one direction [40]. If co-integration does not exist between variables, standard VAR in difference form is applied [36]. If co-integration exists between variables, Engle and Granger [18] propose that the VEC model can be used to test Granger causality for at least one direction (also see Oxley and Greasley [41]). The general VECM form is presented as follows:

\[
\Delta X_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} + \sum_{j=1}^{q} \gamma_j \Delta Y_{t-j} + \delta \text{ECT}_{t-1} + \mu_t
\]

\[
\Delta Y_t = \alpha + \sum_{i=1}^{r} \beta_i \Delta X_{t-i} + \sum_{j=1}^{s} \gamma_j \Delta Y_{t-j} + \varepsilon \text{ECT}_{t-1} + \nu_t
\]

where \( X_t \) and \( Y_t \) represent the seasonally adjusted GDP and ELEC in logarithmic form, \( \Delta X_t, \Delta Y_t \) are the differences in variables, and \( \beta_i \) & \( \gamma_j \) and \( \beta_i \) & \( \gamma_j \) capture the short-term relationships respectively. The \( \mu_t, \nu_t \) are the serially uncorrelated error terms. The \( \text{ECT}_{t-1} \) is derived from the long-run co-integration relationship. The optimum lag lengths \( p, q, r, s \) are determined based on Schwartz Information Criteria.

This specification allows us to test for both short-run and long-run causality. For example, electricity consumption does not Granger cause the growth in GDP in the short-run if and only if all the coefficients \( \gamma_j \) are equal to zero in Eq. (8). On the other hand, the growth in GDP does not Granger cause electricity consumption if and only if all the coefficients \( \beta_i \) are equal to zero in Eq. (9). The presence of long-run causality can be established by examining the significance of the coefficient of the error correction term, \( \text{ECT}_{t-1} \) in Eqs. (8) and (9) using a t-test. Finally, we conduct a joint test of \( \text{ECT}_{t-1} \) and the respective interactive terms in Eqs. (8) and (9) using joint F-statistics.

However, if the data are (1) but not co-integrated, VAR can be applied to the data generated by taking the first-order difference of the variables as shown below [36,41]:
\[ \Delta X_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} + \sum_{j=1}^{q} \gamma_j Y_{t-j} + \mu_t \]  
\[ \Delta Y_t = \alpha + \sum_{i=1}^{r} b_i \Delta X_{t-i} + \sum_{j=1}^{s} c_j Y_{t-j} + \nu_t \]

3.5. Accuracy of VEC models

VEC models do not only describe the causal relationships between endogenous variables, they also present the vector error correction form of dependent variables, i.e. gross domestic product and electricity consumption when the variables are co-integrated in the study, as a function of their past values and exogenous variables. The VEC equations can be used to regenerate time series of dependent variables. As suggested by Lai et al. [12], we adopted the mean squared error (MSE) and the mean absolute error (MAE) to evaluate the accuracy of VEC models. The formulation of MSE and MAE is given as follows:

\[ MSE = \frac{1}{T} \sum_{t=1}^{T} e_t^2 \]
\[ MAE = \frac{1}{T} \sum_{t=1}^{T} |e_t| \]

where \( e_t \) is the error defined as the difference between the actual value and the predicted value using the VEC models.

4. Data and the empirical findings

4.1. Data sources and definition of variables

In this study, we focused on determining the causal relationship between gross domestic product (GDP) and electricity consumption (ELEC), and determined to what extent the number of tourists (TOUR) and population (POP) affect the relationship in the world gaming center. As GDP data was only available on a quarterly basis, we obtained the values of ELEC and TOUR based on quarterly data while POP was taken as the number of residents at the end of each quarter. The values of GDP, ELEC, TOUR and POP for the period of 1999 Quarter 1–2008 Quarter 4 were collected from the Principle Statistical Indicators of Macao published by Macao’s Statistics and Census Service.

ELEC was expressed in terms of kilowatt-hour (kWh) while economic output was characterized by GDP in 2002 prices, using GDP deflators. These variables were transformed to logarithmic values, namely LGDP, LELEC, LTOUR and LPOP, and logarithmic seasonally adjusted values, namely LGDPSA, LELECSA and LTOURSA, before tests were performed as suggested by Pao [33] for quarterly data. Figs. 1 and 2 show the plots of LGDP, LGDPSA, LELEC & LELECSA and LTOUR, LTOURSA & LPOP respectively. They show that GDP, ELEC, TOUR and POP grew between 2001 and 2008, especially after the opening of Sands Macao—a mega casino in May 2005. However, there was a substantial drop in TOUR in the 2nd quarter of 2003 because the outbreak of Severe Acute Respiratory Syndrome (SARS) in Asia. Since the aim of the study was to explore the causal relationship between electricity consumption and economic growth, LGDPSA and LELECSA were set as endogenous variables and LTOURSA and LPOP as exogenous variables in causal analysis. As data magnitude might have an effect on the analysis of causal relationship between variables, time series data were processed by logarithmic transformation and tests were repeated using different combinations of endogenous and exogenous variables, namely LGDPSA, LELECSA, LTOURSA and LPOP. The computer software employed in the study was Eviews 6.0.

4.2. Results from unit-root tests

Table 2 presents the results of the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit-root tests for the two endogenous and two exogenous variables used in the analysis. In each test, we included a constant in the auto-regressive model.

According to the ADF results shown in Table 2, the null hypotheses could not be rejected even at the 5 percent level for LGDPSA, LELECSA, LTOURSA, and LPOP in levels but the null hypotheses were rejected at the 1 or 5 percent level for LGDPSA, LELECSA, LPOP and LTOURSA in first and second differences. Therefore, the ADF statistics show that all investigated variables including LGDPSA, LELECSA, LPOP and LTOURSA were integrated of order one, \( I(1) \), which are normal for typical economic parameters. Similar conclusions were obtained from the Phillips–Perron (PP) unit-root tests. The null hypotheses were not rejected at the 5 percent level for LGDPSA, LELECSA, LPOP and LTOURSA in levels but were rejected at 1 or 5 percent level for LGDPSA, LELECSA, LPOP and LTOURSA in first and second differences, which indicated an integration order of \( I(1) \). The result of this PP unit-root test for all parameters (i.e. \( I(1) \)) are the same to that of ADF unit-root test (i.e. \( I(1) \)).
co-integration relationships among endogenous and exogenous variables. The co-integration analysis is typically applied to verify if there exists a long-run relationship between variables respectively [43–45]. Based on the previous results of Johansen co-integration tests, two endogenous and exogenous combinations (i.e. LELECSA & LGDPSA and LELECSA & LGDPSA & LTOURSA) were selected for vector error correction (VEC) modeling. However, the combinations with the endogenous variable LPOP did not show co-integration and the major purpose of this analysis is to determine the causality between LELECSA and LGDPSA, the analyses for the combinations with LPOP would not further be conducted. The appropriate lag numbers of different endogenous and exogenous combinations were determined using the minimum Schwartz Information Criterion (SIC). Since the appropriate lag number of these VEC models was 1, we tried different combinations of lag numbers from 1 to 3 in VEC models for comparison.

4.4. VEC-based Granger causality test

After having verified the co-integration properties of the variables, vector error correction models were applied to the first-difference variables to determine the long-run and short-run relationships between variables respectively [43–45]. Based on the previous results of Johansen co-integration tests, two endogenous and exogenous combinations (i.e. LELECSA & LGDPSA and LELECSA & LGDPSA & LTOURSA) were selected for vector error correction (VEC) modeling. However, the combinations with the endogenous variable LPOP did not show co-integration and the major purpose of this analysis is to determine the causality between LELECSA and LGDPSA, the analyses for the combinations with LPOP would not further be conducted. The appropriate lag numbers of different endogenous and exogenous combinations were determined using the minimum Schwartz Information Criterion (SIC). Since the appropriate lag number of these VEC models was 1, we tried different combinations of lag numbers from 1 to 3 in VEC models for comparison.

Three major criteria were adopted to compare various VEC models. They were the goodness of fit, stability and causality. First, the goodness of fit of a VEC model describes how well the regenerated data fit a set of observations as it measures the variability between the actual data and the estimated data using VEC equations. The adjusted coefficient of determination (adjusted $R^2$) was used to indicate the goodness of fit of the model investigated. The higher adjusted $R^2$, the better goodness of fit. Moreover, the stability of VEC models is a statistical property of continuity to estimate the stable distributions provided by a linear combination of variables in models. For example, structural changes and/or discontinuities in the data typically may cause unstable in estimated models. In VEC models, we applied unit-root tests for determining model stability. Furthermore, t-tests and Wald tests were applied to test whether the long-run relationships and short-run causalities exist in VEC models. In Wald tests, chi-square $\chi^2$ statistics and their probabilities were obtained to determine the short-run causalities in VEC models, respectively. When the probability of chi-square statistics was below 5 percent, the null hypothesis was rejected based on the 5 percent significance level, implying a VEC model having a short-run causal relationship between dependent and independent variables.

Tables 4 and 5 show the VEC findings and the endogeneity of models with the goodness of fit, stability test and causality test, and the final VEC model, respectively. Based on the same three criteria of model selections, all VEC models with endogenous variables $\Delta$LGDP & $\Delta$LELECSA and $\Delta$LGDP & $\Delta$LPOP & $\Delta$LTOURSA did not have co-integration relationships (in Table 3, $H_0: r = 0$, $r \leq 1$ and $c \leq 2$ were accepted at the 5 percent critical level) but LELECSA & $\Delta$LGDP & some model had one or more than one co-integration equations (in Table 4, $H_0: r = 0$ or $r = 0$ & $r \leq 1$ were rejected at the 5 percent critical level). The optimum lag lengths for different combinations of endogenous and exogenous variables, as shown in Table 3, were determined using the minimum Schwartz Information Criterion (SIC) through unconstrained VAR estimation.

| Table 2 |
| --- |
| Unit-root tests |
| Variable | Augmented Dicker Fuller | Phillips–Perron |
| --- | --- | --- |
| Lag length | t-Statistics | t-Statistics |
| Level | LGDPSA | 0 | -0.223 (<0.93) | -0.178 (<0.93) |
| | LELECSA | 0 | -1.551 (<1.00) | -1.779 (<1.00) |
| | LPOP | 1 | -0.382 (<0.98) | -1.954 (<1.00) |
| | LTOURSA | 1 | -0.482 (<0.88) | -0.528 (<0.87) |
| First-difference | $\Delta$LGDPSA | 0 | -6.496 (<0.01)* | -6.500 (<0.01)* |
| | $\Delta$LELECSA | 0 | -6.671 (<0.01)* | -6.638 (<0.01)* |
| | $\Delta$LPOP | 0 | -2.930 (0.05)** | -2.952 (0.05)** |
| | $\Delta$LTOURSA | 0 | -8.792 (<0.01)* | -10.671 (<0.01)* |
| Second-difference | $\Delta^2$LGDPSA | 0 | -11.454 (<0.01)* | -14.592 (<0.01)* |
| | $\Delta^2$LELECSA | 0 | -12.441 (<0.01)* | -36.927 (<0.01)* |
| | $\Delta^2$LPOP | 0 | -6.687 (<0.01)* | -6.721 (<0.01)* |
| | $\Delta^2$LTOURSA | 1 | -8.498 (<0.01)* | -31.021 (<0.01)* |

Notes: For ADF tests, the optimal lag length was determined using Schwartz Information Criteria. The critical values of the ADF statistic at the 0.01, and 0.05 levels are –4.334, and –3.603 respectively (see MacKinnon [42]). * and ** denote the rejection of the null hypothesis at the 1 percent and 5 percent significance value, respectively. Number in parentheses are the corresponding p-values.

| Table 3 |
| --- |
| Johansen and Juselius co-integration tests |
| Variables | Null | Optimal lag | Test statistics |
| --- | --- | --- | --- |
| | Trace statistics | Maximum eigenvalue |
| LELECSA and LGDPSA & LTOURSA | r = 0 | 1 | 22.95* | 19.89* |
| | r = 1 | 3.06 | 3.06 |
| LELECSA, LGDPSA and LPOP & LTOURSA | r = 0 | 1 | 28.98 | 17.61 |
| | r = 1 | 11.36 | 7.99 |
| | r = 2 | 3.37 | 3.37 |
| LELECSA, LGDPSA and LTOURSA | r = 0 | 1 | 36.54* | 23.82* |
| | r = 1 | 12.72 | 9.03 |
| | r = 2 | 3.69 | 3.69 |
| LELECSA, LGDPSA, LPOP and LTOURSA | r = 0 | 1 | 50.90 | 28.44 |
| | r = 1 | 22.46 | 11.44 |
| | r = 2 | 11.01 | 6.18 |
| | r = 3 | 4.83 | 4.83 |

Notes: The optimal lag lengths are chosen using Schwartz Information Criteria. * denotes the rejection of the null hypothesis at the 5 percent significance value. # denotes the co-integration method used as follows: #1. No intercept or trend in co-integrating equation (CE) or VAR, #2. Intercept (no trend) in CE, no intercept or trend in VAR, #3. Intercept in CE and VAR, no trends in CE and VAR, #4. Intercept in CE and VAR, linear trend in CE, no trend in VAR, and #5. Intercept and quadratic trend in CE and intercept and linear trend in VAR.

4.3. Co-integration analysis

As all variables LGDPSA, LELECSA, LPOP and LTOURSA were non-stationary in levels based on ADF and PP unit-root tests, co-integration test was used to check whether a linear combination of two or more non-stationary series is stationary. The co-integration analysis is typically applied to verify if there exists a long-run relationship between the variables. The results for the Johansen maximum likelihood tests on the unrestricted models are shown in Table 3. Table 3 presents maximum eigenvalues and trace statistics and shows the co-integration relationships among endogenous and exogenous variables. The results of Johansen co-integration tests indicate that LELECSA & LGDPSA & LPOP and LELECSA & LGDPSA & LTOURSA did not have co-integration relationships (in Table 3, $H_0: r = 0$, $r \leq 1$ and $c \leq 2$ were accepted at the 5 percent critical level) but LELECSA & LGDPSA & some model had one or more than one co-integration equations (in Table 3, $H_0: r = 0$ or $r = 0$ & $r \leq 1$ were rejected at the 5 percent critical level). The optimum lag lengths for different combinations of endogenous and exogenous variables, as shown in Table 3, were determined using the minimum Schwartz Information Criterion (SIC) through unconstrained VAR estimation.
the VEC model with endogenous variables $\triangle LGDPSA$ & $\triangle LELECSA$, exogenous variable $C$ and lag number 1, were acceptable. Therefore, the VEC model with endogenous variables $\Delta LGDPSA$ & $\Delta LELECSA$, exogenous variables $C$ and lag number 1, was found to be the more appropriate one to describe the situation in Macao SAR. On the other hand, we then continued to perform t-test on the error correction term $ECT_{t-1}$ for long-run causality and joint $F$ test to determine whether short-run adjustment would re-establish long-run equilibrium or not. In Table 7, in VECM equations, the probability of the error correction term $ECT_{t-1}$ in $\Delta LGDPSA$ and $\Delta LELECSA$ equations by t-test is 0.6077 and 0.0072 respectively. The results indicated that there was a unidirectional long-run causality from $LGDPSA$ to $LELECSA$ (i.e. $LGDPSA \rightarrow LELECSA$ in the long-run). Moreover, the joint $F$ test for the sum of lagged terms of each explanatory variable (i.e. $\Delta LGDPSA$ and $\Delta LELECSA$) and $ECT_{t-1}$ term in $\Delta LGDPSA$ and $\Delta LELECSA$ equations evaluated whether short-run adjustment to re-establish long-run equilibrium, given a shock to the system. The results in Table 6 show that the joint significance of $\Delta LGDPSA$ and $ECT_{t-1}$ term in $\Delta LELECSA$ equation existed but that of $\Delta LELECSA$ and $ECT_{t-1}$ term in $\Delta LGDPSA$ equation did not exist. This implies that electricity consumption and gross domestic product interact in the short-term to restore long-term equilibrium after a change in gross domestic product. The situation is mainly caused by change in the number of tourists (and their spending behaviors) affecting electricity consumption and gross domestic product at the same time. And after a longer period, the responses in electricity consumption and gross domestic product become stable and restore the equilibrium between electricity consumption and gross domestic product.

Overall, the $\Delta LGDPSA$ & $\Delta LELECSA$ VEC models indicated a long-run causality and joint short/long-run causality from gross domestic product to electricity consumption ($\Delta LGDPSA \rightarrow \Delta LELECSA$ in the long-run), but no short-run causality existed. They represent that short-run and long-run relationships are different. The $\Delta LGDPSA$ equation indicated that there was no short-run, long-run and joint short/long-run causality. The $\Delta LELECSA$ equation, however, indicated that there was a long-run (and joint short/long-run) causality but no short-run causality. These results indicated that although no short-run causality from gross domestic product to electricity existed, short-run interaction can lead to a long-run causality. Moreover, the long-run causality from gross domestic product to electricity existed significantly. The VEC model shown in Table 7 is given as follows:

$$\Delta LGDPSA = -0.0524*(\Delta LGDPSA(-1)) - 1.2085*\Delta LELECSA(-1) + 2.6502 – 0.1483*\Delta LGDPSA(-1) + 0.3607*\Delta LELECSA(-1) + 0.0239$$

$$\Delta LELECSA = -0.1390*(\Delta LGDPSA(-1)) - 1.2085*\Delta LELECSA(-1) + 2.6503 – 0.1255*\Delta LGDPSA(-1) – 0.1083*\Delta LELECSA(-1) + 0.0264. 3$$

The results of VEC shown in Tables 4–6 matched with the results of co-integration tests shown in Table 3. Based on these analyses, we conclude that there was a unidirectional long-run relationship from gross domestic product to electricity consumption.
Table 6  
Estimation results of joint test for logarithmic series of seasonally adjusted GDP and electricity consumption.

| Source of causality | Joint short/long-term test | ΔGDPSA and ECT | ΔELECSA and ECT |
|---------------------|---------------------------|----------------|-----------------|
| F-statistics        |                            |                |                 |
| ΔGDPSA              | –                         | 0.6512         |                 |
| ΔELECSA             | 4.1797**                  | –              |                 |

Notes: 1. ΔGDPSA and ΔELECSA are the first-difference series of LGDPSA and LELECSA respectively; ECT is the Error Correction Term. Δ denotes first-difference of variables. 2. * and ** denote the rejection of the null hypothesis at the 1 percent and 5 percent significance value, respectively.

4.5. Error analysis of VEC models

Eqs. (14) and (15) were used to regenerate the values of ΔGDPSA and ΔELECSA for the period of 1999 Quarter 3–2008 Quarter 4. The regenerated data were then compared to the actual data and the MSE and MAE were determined using Eq. (12) and (13). The values of MSE and MAE were 0.0038 and 0.0433 for ΔGDPSA and 0.0008 and 0.0224 for ΔELECSA respectively, as shown in Table 7. One-sample F-tests show that the values of squared error and the values of absolute error of ΔGDPSA and ΔELECSA were not significantly different from zero at the 95 percent level of confidence. The results illustrate that VEC models reproduced time series of ΔGDPSA and ΔELECSA accurately.

5. Concluding remarks and implications

Co-integration analyses show that there was a co-integrated relationship between seasonally adjusted electricity consumption and economic growth (LELECSA and LGDPSA) in Macao over the period of 1999 Quarter 1–2008 Quarter 4. Vector error correction models indicated that there was a long-run unidirectional causal relationship from gross domestic product to electricity consumption. Moreover, given a change in gross domestic product, gross domestic product and electricity consumption interacted in short-term and then re-established the long-run equilibrium. Co-integration test showed that seasonally adjusted gross domestic product, electricity and tourists’ amount in natural log scale (LGDPSA, LELECSA and LTOURSA) were co-integrated. Although in previous section, we adopted the VEC model with ΔGDPSA and ΔELECSA only, change in the number of tourists (ΔTOURSA) will have a peculiar effect on ΔGDPSA than on ΔELECSA. It can be understood because the gaming and tourism center in Asia Macao SAR depends heavily on the tourism industry (but in fact more on the high rollers among those tourists). The number of tourists (more specifically, the number of high rollers) affects significantly and positively on gross domestic product and in turn affects electricity consumption. A detailed observation of the ΔLELECSA VEC equation reveals that ΔELECSA depends heavily and significantly on the lag 1 of ΔGDPSA. This implies that in a service-oriented territory, infrastructures such as casinos, hotels, resorts, convention centers, food-serving outlets, etc. have to be built (leading to a sudden increase in GDPSA) and operated to attract tourists, consequently leading to a positive change in the city’s or national electricity consumption.

The results provide useful information to policy makers in other Asian cities or countries. First, a city can enjoy the economic growth brought by the development of the gaming and tourism industry but policy makers have to find ways to produce and utilize their electricity more environmentally friendly and efficiently. It is because the depletion of energy resources and the emission of carbon dioxide—a major greenhouse gas—are recognized as international problems. Nevertheless, it is possible that operators of entertainment venues can adopt a wide range of energy saving practices, such as adopting variable speed drives for fans, pumps and lifts, introducing heat exchangers and heat pumps in air-conditioning and refrigerating systems, and adopting energy-efficient and yet cost effective and environmental-friendly commercial applicants [46], etc. Second, whether the gaming industry will bring negative impacts on social and cultural systems is debatable [47]. Macao’s economic development in recent years is eye-opening. However, the number of young problem gamblers has increased over time.

Acknowledgment

The authors gratefully acknowledge support of this work by the Macao Polytechnic Institute through Grant P014/DECP/2009. We also thank anonymous reviewers for many valuable comments that improve the paper greatly.

References

[1] DICJ. Gaming statistical information of Macao. Macao Gaming Inspection and Coordination Bureau. See also: http://www.dicj.gov.mo/web/cn/information/DadosEstat2009/content.html#11; 2009.
[2] Houthakker HS. Some calculations on electricity consumption in Great Britain. J R Stat Soc Ser A — Gen 1951;114(3):359–71.
[3] Foss MR. The utilization of capital equipment: postwar compared with prewar. Survey of Current Business, Washington D.C., Bureau of Census, 1963:8–16.
[4] Jorgensen DW, Griliches Z. The explanation of productivity change. Rev Econ Stud 1967;34:249–83.
[5] Heathfield DF. The measurement of capital usage via electricity consumption data for the UK. J R Stat Soc Ser A — Gen 1972;135(2):208–20.
[6] Mount TD, Chapman LD, Tymrell TJ. Electricity demand in the US: an econometric analysis. Oak Ridge, TN: Oak Ridge National Laboratory; 1973.
[7] Ranjan M, Jain VK. Modeling of electrical energy consumption in Delhi. Energy 1995;24:351–61.
[8] Egoliouf M, Mohammad AA, Guven H. Economic variables and electricity consumption in North Cyprus. Energy 2001;26:355–62.
[9] Nair GE, Barid EA, Younes MR. Neural networks in forecasting electrical energy consumption: univariate and multivariate approaches. Int J Energy Res 2002;26:67–78.
[10] Ozturk HK, Ceylan H. Forecasting total and industrial sector electricity demand based on genetic algorithm approach. Turkey case study. Int J Energy Res 2005;29:829–40.
[11] Pao HT. Comparing linear and nonlinear forecasts for Taiwan’s electricity consumption. Energy 2006;31:2129–41.
[12] Lai TM, To WM, Lo CW, Choy YS. Modeling of electricity consumption in the Macao SAR’s economic development in recent years is eye-opening. However, the number of young problem gamblers has increased over time.
[21] Cheng BS, Lai WT. An investigation of co-integration and causality between energy consumption and economic activity in Taiwan. Energy Econ 1997;19:435–44.

[22] Glasure YU, Lee AR. Cointegration, error correction and the relationship between GDP and energy: the case of South Korea and Singapore. Res Energy Econ 1998;20:17–25.

[23] Yang HY. A note on the causal relationship between energy and GDP in Taiwan. Energy Econ 2000;22(3):309–17.

[24] Hondooyianni G, Lolos S, Papapetrou E. Energy consumption and economic growth assessing the evidence from Greece. Energy Econ 2002;24:319–36.

[25] Ghosh S. Electricity consumption and economic growth in India. Energy Policy 2002;30(2):125–9.

[26] Shiu A, Lam PL. Electricity consumption and economic growth in China. Energy Policy 2004;32(1):47–54.

[27] Oh WK, Lee KH. Energy consumption and economic growth in Korea: testing the causality relation. J Policy Mod 2004;26:973–81.

[28] Wolde-Rufael Y. Electricity consumption and economic growth: a time series experience for 17 African countries. Energy Policy 2006;34(10):1106–14.

[29] Yoo SH. The causal relationship between electricity consumption and economic growth in the ASEAN countries. Energy Policy 2006;34:3573–82.

[30] Yuan J, Zhao C, Yu S, Hu Z. Electricity consumption and economic growth in China: cointegration and co-feature analysis. Energy Econ 2007;29:1179–91.

[31] Lee CC, Chang CP. Energy consumption and GDP revisited: a panel analysis of developed and developing countries. Energy Econ 2007;29:1206–23.

[32] Chontanawat J, Hunt LC, Pierse R. Does energy consumption cause economic growth? Evidence from a systematic study of over 100 countries. J Policy Model 2008;30(2):209–20.

[33] Pao HT. Forecast of electricity consumption and economic growth in Taiwan by state space modeling. Energy 2009;34:1779–91.

[34] Warr BS, Ayres RU. Evidence of causality between the quantity and quality of energy consumption and economic growth. Energy 2010;35:1688–93.

[35] Johansen S. Statistical analysis of cointegration vectors. J Econ Dyn Cont 1988;12:231–54.

[36] Granger CW. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 1969;37(3):424–38.

[37] Dickey DA, Fuller WA. Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 1979;74:427–31.

[38] Phillips PCB, Perron P. Testing for a unit root in time series regression. Biometrika 1988;75:335–46.

[39] Verbeek M. A guide to modern econometrics. 2nd ed. Chichester: John Wiley & Sons; 2004.

[40] Granger CWJ. Some recent developments in a concept of causality. J Econometrics 1988;39:199–211.

[41] Oseley L, Geasly D. Vector autoregression, cointegration and causality: testing for causes of the British industrial revolution. Appl Econ 1998;30:1387–97.

[42] MacKinnon JG. Numerical distribution functions for unit root and cointegration tests. J Appl Econometrics 1996;11(6):601–18.

[43] Toda HY, Yamamoto T. Statistical inference in vector autoregressions with possibly integrated process. J Econometrics 1995;66(1–2):225–50.

[44] Zapata HO, Rambaldi AN. Monte Carlo evidence on cointegration and causation. Oxford Bull Econ Stat 1997;59(2):285–98.

[45] Kanioura A, Turner P. Critical values for an F-test for cointegration in the multivariate model. Appl Econ 2005;37(3):265–70.

[46] To WM, Yu TW, Lai TM, Li SP. Characterization of commercial clothes dryers based on energy-efficiency analysis. Int J Clothing Sci Technol 2007;19(5):277–90.

[47] Iwan FVC. Changes in residents’ gambling attitudes and perceived impacts at the fifth anniversary of Macao’s gaming deregulation. J Travel Res 2009;47(3):388–97.