Electricity Consumption and Economic Activity in Malaysia: Co-integration, Causality and Assessing the Forecasting Ability of the Vector Error Correction Model

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ABSTRACT

The paper empirically investigates the co-integration and causality relationship between electricity consumption (EC) and income based on Malaysia's data over the period 1980-2014 using VECM's framework. In the analysis, the paper used standard econometric approach, namely the unit root tests, the co-integration tests, and Granger causality tests. Meanwhile, to evaluate the forecasting ability, the paper used variance decomposition analysis and standard diagnostic tests for accessing the forecast ability. The paper provides empirical evidence on the existence of short-and long-run unidirectional causality relationship running from economic activity to EC in Malaysia. The results from variance decomposition analysis suggested that economic activity is an important variable in explaining future variation in EC of the country. The forecasting diagnostic tests showed that the VECM has a good forecasting ability to forecast EC for Malaysia. In this respect, the usage of more sophisticated econometric techniques such as the co-integration approach and the VECM should be considered. The existence of unidirectional causality running from economy activity to EC may suggest that the government can implement electricity conservation measures without putting economic development at risk.

Keywords: Economic Activity, Electricity Consumption, Vector-error Correction Model
JEL Classifications: O43, Q43, Q47

1. INTRODUCTION

Electricity energy is a crucial element in the development process as well as economic growth of a country. Shortage of electricity supply may negatively affect the development progress of the country, and possibly limit its potential growth. On the other hand, over supplies of electricity is a waste to the economy since the surplus cannot be stored as inventory. Therefore, a good forecasting technique is critically important to estimate the level of electricity's demand accurately, thus proper planning could be made by the utility company and the government in order to meet country's future energy demand.

In-line with the growth in the electricity consumption (EC), many empirical studies has been conducted to forecast the medium- and long-term demand for electricity. For this purpose, several time series forecasting techniques, such as autoregressive (AR) technique, moving average (MA) algorithm, general exponential

smoothing algorithm, ARMA algorithm, and AR integrated MA (ARIMA) were applied. These time series methods have been widely accepted in forecasting demand for electricity, particularly in developed countries (Zhang, 1987). However, the performance of these forecasting techniques in the case of developing economy is still doubtful. This is because differences in the nature of growth, socioeconomic conditions, and subsidized energy tariffs can significantly impact the demand (Baraket and Eissa, 1987).

The objective of this paper is to evaluate a forecasting model for the aggregate demand of EC in Malaysia using co-integration approach in the framework error correction model (ECM). The reasons for adopting co-integration approaches in estimating demand for electricity are twofold. First, earlier econometric studies on electricity demand were subjected to spurious regression (Greene, 2000), which occurred when variables that are driven by time trends appear to be correlated in finite sample regression even though no true relationship exists among them. Second, since the

economic variables employed in the electricity demand equation are likely to be endogenous, estimating electricity demand by a single equation may produce simultaneous bias, hence leading to unreliable forecast. Both problems, however, could be overcome with the use of the co-integration approach. On top of that, the co-integration technique can identify the long-term equilibrium relation among variables, should they exist.

There are several studies have been conducted to empirically examine the causality and co-integration relationship between energy consumption (EC) and economic activity, either using VAR or VECM approach. For instance, by Masih and Masih (1996; 1997), Cheng and Lai (1997), Asafu-Adjave (2000), Yang (2000), Hondroyiannis et al. (2002), Soytas and Sari (2003), Oh and Lee (2004), Lee (2005; 2006), Fang (2011), Apergis and Payne (2010), and Pao and Fu (2013). However, none of these studies examine the forecasting ability of the VECM models. Therefore, this paper intends to extend the existing empirical literature in this issue by examining the forecasting ability of the ECM in forecasting the level of EC and gross domestic product (GDP) based on Malaysia's data. This paper, however, is not intended to compare the forecasting ability with the forecasting model that is currently in used.

2. ELECTRICITY INDUSTRY AND ELECTRICITY FORECASTING PRACTICES

In Malaysia, prior to 1990's, the main electricity power provider is Tenaga Nasional Berhad (TNB). However, by mid-1990's, the Malaysian government allowed private companies to participate in the generation sector through the introduction of Independence Power Producer (IPPs). The IPPs were given licenses to supply electricity to TNB through negotiated power purchase agreements. Transmission and distribution networks, however, remained under the control of TNB. The structure of the industry remained the same until now with TNB and IPPs as the main players of the generation sector (Malaysia EC, 2013).

TNB was established in September 1990 through a corporatization and privatization exercise by the Malaysian government. As of December 2013, TNB has more than RM99 billion in assets and serving over 8.4 million customers throughout the Peninsular, Sabah and Labuan. The core activities of TNB are generation, transmission and distribution of electricity. TNB is the main provider in electricity generation in Malaysia through its wholly owned subsidiary; TNB Generation Sdn. Bhd. TNB has a total of over 9000MW installed generation capacity that accounts for over 41% of the total power generation in Peninsular Malaysia (TNB, 2013).

Forecasting a demand for electricity is one of the most important functions in power system planning and development. This is due to the fact that in this industry, the gap in the lead times between decision making and its implementation is very long. This is further complicated with the nature of the product i.e. electricity, which cannot be stored (in large volume). This industry is also a capital intensive industry. Therefore, a good demand forecast for

electricity is important since the consequences of under or over forecasting are serious.

At TNB, demand forecast, also know as Long Term Load Forecast, plays a central role especially in planning the electric power system. This forecast was prepared by Load Forecast Unit, which is under the planning division of TNB. The forecast load will be up to 20 years ahead with focus on annual total sales, peak demand, and energy generation. In addition, TNB also conduct sectoral sales forecast such as for industrial, commercial, domestic, mining, public lighting and agriculture sector (Malaysia EC, 2013).

The long term load forecasting process is implemented through the use of industry-wide practice techniques. Analyses are made from macro and micro perspectives, utilizing both top-down and bottom-up approaches. The most recent economic data, information on electricity demand and technical and socio demographic data were used as inputs for the analysis. While key input to the forecast is the GDP, other important variables used are load factor, losses, electricity price, population, and energy efficiency. The forecast for electricity sales, generation and peak demand are established based on various assumptions on the Malaysian economic and demographic development, as well as technical parameters (Malaysia EC, 2013).

3. LITERATURE REVIEW

The demand for electricity has been among the most popular modeling exercises for the past few years. While most economists believe that they understand the concept underlying electricity demand; in practice, however, problems such as limited data, measurement for theoretical variables and differences in purposes have led to a wide range of variety of approaches. There is the `all fuels' approach, which estimates total demand then allocates the demand to single fuels based primarily on relative prices. Another method is the end use engineering model, which constructs an estimate of total electricity demand from estimations of the stock of appliances, and engineering estimates of electricity use per appliance. This approach, however, is only suitable for short term. Since the demand forecast on EC need to be done over a long period, this method cannot be used. Another popular method that is usually used in forecasting future requirements of electricity is the time series analysis, which uses time as the only variable. This is based on the observations from all over the world that the consumption of electricity has developed practically in regular manner over long periods. This observation has led to the belief that electricity demand is exempted from random factors affecting the rest of the economy, and the electricity supply benefits from the privilege of being a generator of its own growth rate/time.

Besides time series analysis, econometric models are also popular methods used by researchers in forecasting the demand for electricity. A number of econometric models have been developed where economic, social, geographic, and demographic factors are used as the independent variables. For example, Mohamed and Bodger (2005), in their study on EC in New Zealand, used GDP, electricity price, and population size as independent variables in their linear regression model. They found that EC in New Zealand

is significantly correlated with all of the variables. Harris and Liu (1993) found that the price of electricity is a major factor in explaining conservation behavior of consumers towards EC. Rajan and Jain (1999) found that the EC patterns for Delhi depend on weather and population. Fung and Tummala (1993) concluded in their study that it is reasonable to use electricity price, GDP, deflated domestic exports and population to forecast EC in Hong Kong.

Dahl (1994), in his survey, found that most of the studies on electricity demand used static or partial adjustment models. Jones (1993) compared the forecasting ability of the static and partial adjustments model with the general to specific (GTS) or dynamic regression model and found that the GTS approach was a more superior forecast model. However, Chan and Lee (1997) argued that the GTS approach may overlook the fact that most of the time series data are non-stationary. Their study show that the Engle-Granger approach outperforms Hendry's ECM and Hendry's general-to-specific approach in terms of having the smallest ex post forecast errors. Besides the study by Chan and Lee (1997), several other empirical studies also used ECM approach. Asafu-Adjaye (2000), for instance, estimated the causal relationship between EC and income for India, Indonesia, the Philippines and Thailand, using cointegration and error-correction modeling techniques. He found an unidirectional Granger causality runs from energy to income for India and Indonesia, while bidirectional Granger causality runs from energy to income for Thailand and the Philippines. Hondroyiannis et al. (2002) used VECM approach to empirically examine the relationship between EC and economic growth in Greece. The VECM specification includes EC, real GDP and price developments-a measurement for economic efficiency. The empirical evidence suggested that there is a long-run relationship between the three variables.

In term of causality, several studies find a bidirectional relationship between renewable EC and economic growth. Soytas and Sari (2003), for example, examined the causality relationship between EC and GDP in the top 10 emerging markets and G-7 countries, using ECM. They discovered bi-directional causality in Argentina, causality running from GDP to EC in Italy and Korea, and from EC to GDP in Turkey, France, Germany and Japan. Pao and Fu (2013) examine the casual relationship between economic growth and aggregated and disaggregated renewable EC in the case of Brazil. They found mixed results regarding the direction of causality between the variables. Ozturk and Acaravci (2011) studied the causality between EC and economic growth in the 11 Middle East and North Africa countries and found cointegration and causality relationship in four countries (Egypt, Israel, Oman and Saudi Arabia). Moreover, in their study on the short-run and long-run relationship between EC and economic growth for Turkey, Acaravci and Ozturk (2012) found evidence of unidirectional short-run and long-run causalities running from the EC per capita to real GDP per capita. Pei et al. (2016) examined the effects of electric consumption on three sectors, namely, manufacturing, agriculture and services in Malaysia. The results showed that electric consumption does not Granger causes manufacturing and services sectors, but does Granger cause the agriculture sector of Malaysia. Solarin et al. (2016) investigated the relationship

between EC and economic growth in Angola by including exports, imports and urbanization in the production function. They found that EC boots economic growth but urbanization impairs it. Awad and Yossof (2016) examined the nexus between electricity production, economic growth and employment in Sudan. The causality relationship test supported the existence of bi-directional short-run and long-run relationship between energy generation and economic growth.

Meanwhile, several studies have used panel cointegration techniques to examine the casual relationship between renewable EC and economic growth. Lee (2005) investigated the co-integration and causality relationship between EC and GDP through panel data of 18 developing countries. He found evidence of long-run and short-run causalities that run from EC to GDP, but not vice versa. Using a multivariate panel ECM, Apergis and Payne (2010a) found evidence of bidirectional short-and long-run causality between non-hydroelectric renewable EC and economic growth for a panel of 20 OECD countries. In another panel study of nine South American countries, Apergis and Payne (2010b) found both short-and long-run unidirectional causality from EC to economic growth. They also discovered evidence of bidirectional short-and long-run causalities between total renewable EC and economic growth for a panel of 13 Eurasian countries, a panel of six Central American countries, and a panel of 80 countries (Apergis and Payne, 2010c; 2009; 2012). Rezitis and Ahammad (2015) investigated the dynamic relationship between EC and economic growth in nine South and Southeast Asian countries using panel data framework. Their panel Granger causality results proved bidirectional causality effects between EC and economic growth. Contrastingly, in the panel cointegration study of 15 transition countries, Acaravci and Ozturk (2010) found no long-term equilibrium relationship between EC per capita and real GDP per capita.

On top of economic growth, the causality relationship of EC has also been investigated with other economic variables. For example, Salahuddin et al. (2015) investigated the relationship between carbon dioxide, economic growth, EC and financial development (FD) in the Gulf Cooperation Council countries using panel data for the period of 1980-2012. They found EC and economic growth have a positive long run relationship with carbon dioxide emission. Abidin et al. (2015) examined the linkage among EC, foreign direct investment (FDI), FD and trade for the selected ASEAN countries. Results on Granger causality revealed that existence of short-run unidirectional causality runs from FDI inflows to EC, EC to FD, and EC to trade.

4. METHODOLOGY

4.1. Unit Root Tests
The purpose of unit root tests is to establish the stationarity properties of the time series. The existence of unit roots in a variable denotes that series are not stationary. In this paper, the unit root tests are performed using the Augmented Dickey-Fuller (ADF) tests. As an alternative, this paper will also use the Phillips-Perron (PP) test as suggested by Phillips and Perron (1988).

If a time series y_t becomes stationary after being differenced d times, y_t is integrated of order d and denoted by $y \sim I(d)$. The appropriate number of differencing is called the order of integration. For example, if a time series y_t becomes stationary after being differenced once, y_t is integrated of order 1 and denoted by $y \sim I(1)$. Meanwhile, $\{y_{it}\}$ is said to be co-integrated of order 1, if each of its components is integrated of order 1 (Engle and Granger, 1987), which implies that two variables, y_1 and y_2 are only co-integrated if they were integrated in the same order.

4.2. Co-integration Tests

The basic idea behind co-integration is that, if in the long-run two or more series move closely together even though the series themselves are trended, the difference between them is constant. It is possible to regard these series as a long-run equilibrium relationship, as the difference between them is stationary. Meanwhile, lack of co-integration suggests that such variables have no long-run relationship. In principal, they can wander arbitrarily far away from each other (Dickey et al. 1991). There are two tests for co-integration that are frequently used in empirical studies; the single equation based Engle and Granger (1987) test, and the systems based Johansen (1988) tests.

The Engle and Granger (1987) two-step procedure for modeling the relationship between co-integrated variables received a great deal of attention over the recent years. This approach is attractive because it reduces the number of coefficients to be estimated, thus reduces the problem of multicollinearity. On the other hand, the system method suggested by Johansen (1988) enables us to determine the number of co-integration relations and estimate them by maximum likelihood estimation in a unified framework. Johansen (1988) provides a multivariate alternative approach, which tests for multiple co-integrating vectors. It relies on the relationship between the rank of a matrix and its characteristic roots (eigenvalues). Specifically, if the system has r independent co-integrating relations, then the test for the number of characteristic roots that are not significantly different from unity is given by $\lambda_{trace}(r) = -T\Sigma\ln(1-\lambda_i)$, where, λ_i is the number of estimated values of the characteristic roots and T is the number of usable observations.

The Johansen trace tests for co-integration is testing the null that there are less than or equal to h co-integrating relations ($r \leq h$) against the alternative hypothesis that there are more than h co-integrating relations ($r > h$). Meanwhile, the maximum Eigen value test statistic $\lambda_{max(r, r+1)} = -T\ln(1-\lambda_{it+1})$ can be used to test the null that the number of co-integrating vectors is $r \leq h$ against the alternative that $r = h + 1$. Since the trace test is more robust than the maximum Eigen value test as pointed out by Cheung and Lai (1993), this paper will use the trace statistic.

4.3. Granger Causality

In order to test the causality relationship empirically, it is common to apply the Granger causality test, which was introduced by Granger (1969). In a bivariate framework, the variable y_1 is said to cause the variable y_2 in the Granger sense if the forecast for y_2 improves when lagged variables y_1 are included in the equation.

In general, conventional Granger causality can be represented by the following bivariate system.

$$y_{1t} = \delta_1 + \sum_{i=1}^{m} \beta_i y_{1t-i} + \sum_{i=1}^{n} \theta_i y_{2t-1} + \varepsilon_{2t} \tag{1}$$

$$y_{2t} = \delta_2 + \sum_{i=1}^{q} \Pi_i y_{it-i} + \sum_{i=1}^{r} \varphi_i y_{2t-1} + \varepsilon_{2t} \tag{2}$$

Where, δ_1 and δ_2 are drifts. The coefficients θ_is are relevant for testing Granger causality running from y_2 to y_1 while the coefficient π_is are appropriate for Granger causality test running in the opposite direction. According to the above equations, the null hypothesis, which is "y_2 does not Granger cause y_1" is rejected if the coefficients of θ_is in Equation 1 are jointly significant. The null hypothesis that y_1 does not Granger cause y_2 is rejected if the π_is in Equation 2 are jointly significant. If some of $\theta_i \neq 0$ and some $\pi_i \neq 0$ then there is feedback between y_1 and y_2.

4.4. Vector ECM

Engle and Granger (1987) demonstrated that once variables are co-integrated, a corresponding error-correction representation always exists. This implies that changes in the dependent variable are a function of the levels of disequilibrium in the co-integration relationship that is captured by the error-correction term, as well as changes in other explanatory variables. A consequence of co-integration is that either Δy_{1t} or Δy_{2t} or both must be caused by the lagged error-correction term which itself is a function of y_{1t-1}, y_{2t-1}. In general, the relationship between y_1 and y_2 can be written in vector-ECM (VECM) form as:

$$\Delta y_{1t} = \delta_1 + \sum_{i=1}^{m} \gamma_{1i} \Delta y_{1t-i} + \sum_{i=1}^{n} \beta_{1i} \Delta y_{2t-i} + \sum_{i=1}^{r} \alpha_{1i} ECM_{r,t-1} + U_{1t'} \tag{3}$$

$$\Delta y_{2t} = \delta_1 + \sum_{i=1}^{m} \gamma_{2i} \Delta y_{1t-i} + \sum_{i=1}^{n} \beta_{2i} \Delta y_{2t-i} + \sum_{i=1}^{r} \alpha_{2i} ECM_{r,t-1} + U_{2t} \tag{4}$$

Where, Δ denotes the first-difference of a non-stationary variable. In the VECM, the sources of causation can be exposed through the statistical significance of three different tests. First, from a joint test that is applied to the sum of the lags of each explanatory variable. Second, by a t-test on the lagged ECM term, this is the weak exogeneity test. And third, by a joint test that is applied to the sum of each explanatory variable and the lagged ECM terms (the strong exogeneity test).

It is necessary to address the issue of long run and short-run causality implicit in the ECM represented by Equations 3 and 4. Granger (1986) suggested that the ECM approach should lead to better short-run prediction, and integrate the short-run variations with the long-run equilibrium. In this regard, some researchers suggested that the lagged changes in the independent variable represent the short-run causal impact while the ECM term indicates the long-run causality. In the estimation process, the lag lengths are particularly important as the lag length chosen could significantly alter the result. In all estimations, the Akaike Information Criteria (AIC) is used to determine the optimal lag length.

4.5. Data

The main focus of this paper is on the relationship between EC and income which is a measure of economic activity. However,

previous empirical studies suggest that regression with income, the price of electricity and population size as independent variables will provide appropriate forecasting model for EC. Therefore, in addition to electricity consumption and income, two control variables will be included in the regression: Price level and the size of population. In general, the VAR model for these variables can be written as followed:

$$V = v'[EC_t, GDP_t, CPI_t, POP_t] \qquad (5)$$

Where, EC_t is electric power consumption (KWh) in period t; GDP_t measures total income; price levels is measured by the consumer price index (CPI_t; 2010=100); and POP_t is the total number of population. In this study, CPI is used instead of the price of electricity, based on the fact that electricity price in Malaysia is heavily subsidized, thus the price may not truly reflect the cost of electricity consumption. Data for EC, GDP and POP were taken from Malaysia EC and Department of Statistic, while data on CPI were gathered from World Bank indicator database. The series are annual data covering from 1980 to 2014. In estimation process, all data were transformed to logarithm.

5. DATA ANALYSIS AND FINDINGS

5.1. Results from Unit Root Tests
The first step of the analysis is to determine the stationary property of each variable used in the study. This is because the standard Granger causality test assumes stationarity of the time series examined. If the variables are non-stationary, the implications drawn from the test are invalid. The results of unit root tests from the ADF and PP tests for all series studied are presented in Table 1. Based on ADF and PP tests, we found that all series are not stationary at level. Subsequently, the unit root tests have been carried out at first differences. The results from ADF and PP tests at first difference show that all series are statistically significant at 5% level, indicating the first difference of the series is stationary. Therefore, it is concluded that all variables studied are integrated in order 1, I(1). Therefore, all variables were transformed into first difference in the estimation process.

5.2. Results from Co-integration Tests
Table 2 presents results from Johansen co-integration tests of VAR model, which consists of all the variables used in the study: EC, GDP, CPI, and POP. The trace test results show that there are four co-integration relationships between the variables. Meanwhile, the maximum Eigen value test statistic indicates there are two cointegrating equations at the 0.05 level. The results from co-integration tests indicated the existence of long run relationship between the variables studied.

5.3. Results from Granger Causality Tests
Based on results from unit root tests and co-integration tests, this study used a vector ECM to test for causality among the variables of interest. The Granger causality test was carried out using Wald restriction in order to identify the sources of causation. The results from the tests are presented in Table 3. The test results exhibit evidence to support the existence of short run causality from GDP and POP to EC. Meanwhile, the negative and significant coefficient

Table 1: Results from unit root tests

Variables	Level		1st Different	
	ADF	**PP**	**ADF**	**PP**
EC	−1.3049[1]	−1.1967[2]	−8.2316[2]	−8.2288[2]
	(−2.9540)	(−2.9511)	(−2.9540)*	(−2.9540)*
GDP	−0.9764[0]	−1.0927[5]	−4.6666[0]	−6.5134[2]
	(−2.9511)	(−2.9511)	(−2.9434)*	(−2.9540)*
CPI	−1.1579[5]	−1.5166[3]	−3.9417[4]	−5.1639[2]
	(−2.9678)	(−2.9511)	(−2.9678)*	(−2.9540)*
POP	0.2310[0]	0.4882[2]	−5.7503[0]	−5.7504[1]
	(−2.9511)	(−2.9511)	(−2.9540)*	(−2.9540)*

*Figures in parenthesis is MacKinnon (1996) critical value at 5% level. Figures in [] are optimum lag length based on AIC. EC: Electricity consumption , ADF: Augmented Dickey-Fuller, PP: Phillips-Perron, GDP: Gross domestic product, CPI: Consumer price index, AIC: Akaike Information Criteria

Table 2: Co-integration tests

Intercept in CE and test VAR	H_o	Trace	Critical value 5%	Maximum eigenvalue	Critical value 5%
ΔEC, ΔGDP, ΔCPI, ΔPOP	r=0	75.6715*	47.8561	29.3115*	27.5843
	r≤1	46.3605*	29.3605	25.6544*	21.1316
	r≤2	20.7061*	15.4947	12.3236	14.2646
	r≤3	8.3825*	3.3825	8.3825*	3.8415

*Significant at 5% level. The r denotes the maximum number of cointegrating vectors. Δ denotes first difference. H_o is null hypothesis

of ECM indicates the existence of long run causality. Specifically, there is a long run causality running from GDP, CPI and POP to EC. In contrast, the test results do not support the existence of short-run and long-run causality running from EC to GDP. The significant unidirectional causality relationship runs from GDP to EC suggests that past values of GDP are useful in forecasting the level of EC, but historical data of EC is not useful in forecasting the level of income in Malaysia.

5.4. Variance Decompositions
Table 4 presents the estimates for variance decomposition that derived from the estimated VECM model. The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression and determines how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. Data in Table 4 indicates that a shock in GDP, CPI or POP did not cause the variation in EC in the year 1. The explanatory power of these variables on the variation of EC can only be observed in year 2. Statistics in Table 4 show that in a short run (year 3), a shock in GDP explains only roughly 7.5% of the total variation in EC, and this explanatory power increased to 25.6% by the end of the 5th year. Meanwhile, in the long run (year 10), about 41.1% of the total variation in EC can be explained by GDP. As for comparison, a shock in POP causes 5.5% in the variation of EC at the end of year 3. The explanatory power of POP on the variation of EC has increased to 58.1% at the end of 5th year which is double than the explanatory power of GDP. This explanatory power, however, decreased to 49.4% at the end of forecasting period (year 10) but still slightly higher than GDP.

Meanwhile, with regards to the GDP, the results from variance decomposition analysis show that a shock in EC on the variation

Table 3: Granger causality results based on VECM

Dependent variable	Sources of causation				
	Short run				Long run
	ΔGDP[a]	ΔCPI[a]	ΔPOP[a]	ΔEC[a]	ECM[b]
ΔGDP	-	2.3269 (0.3132)	2.6130 (0.2708)	2.5096 (0.2851)	0.3283 (0.0870)
ΔEC	9.5757 (0.0083)*	1.0038 (0.6054)	13.6124 (0.0011)*	-	−0.1396 (0.0014)*
ΔCPI	0.2658 (0.8755)	-	4.2589 (0.1189)	3.8570 (0.1454)	−0.0659 (0.2353)
ΔPOP	3.4429 (0.1788)	1.6886 (0.4298)	-	0.6763 (0.7131)	1.4739 (0.3411)

* Significant at 5% levels. [a]Chi-square statistics from Wald test. [b]t-statistics. Δ denotes first difference

of GDP can be observed as early as in the year 1. At the end of 3rd year, EC explains about 11.7% of the total variation in the GDP, and this explanatory power, however, decreased to 4.9% by the end of the 5th year. The weak explanatory power of EC on the total variation of GDP continues, reaching only about 3.6% at the end of forecasting period (year 10).

5.5. Forecasting Ability

In the final analysis, we evaluate the forecasting ability of estimated VECM in forecasting the level of electricity consumption (EC) in Malaysia during the study period. The ex-post forecasting ability of the estimated VECM is evaluated by four forecasting diagnostic tests; root mean squared error (RMSE); mean absolute error (MAE); Mean Absolute Percent Error (MAPE); and Theil Inequality Coefficient. The first two forecast error statistics depend on the scale of dependent variable, thus these statistics should be used as relative measures to compare forecasts for the same series across different models-the smaller the error, the better the forecasting ability of the model, according to the criterion. The remaining two statistics are scale-invariant. The Theil inequality coefficient always lies between zero and one, where zero indicates a perfect fit.

The diagnostic statistics for measuring forecasting accuracy for GDP and EC are reported in Table 5. The Theil inequality coefficient of 0.0048 and 0.0040 indicate the high degree of fit of the estimated VECM in predicting the short-run fluctuations in EC and GDP, respectively. The MAPE for EC is 0.67 in comparison to 0.70 in the case of GDP. Other diagnostic statistics also indicate that the ECM used in this study perform relatively better in forecasting the EC compared to GDP. All diagnostic statistics led to the conclusion that the estimated regression with error correction term has a good forecasting ability to forecast electricity consumption for Malaysia.

Figure 1 shows a plot between actual and fitted values based on the estimated VECM for EC. In general, the plot shows that the fitted values of EC are able to track the actual data fairly well. However, the model failed to track a major turning point in electricity consumption in the year 1989. Contradictorily, the plot for GDP in Figure 2 indicates that the fitted values from the model appear to fail to track the actual data reasonably well.

6. DISCUSSION AND CONCLUSION

Forecasting electricity consumption has been the focus of many empirical researches in the past few years. Several forecasting techniques have been applied, ranging from a simple uni-variate

Table 4: Variance decomposition from VECM

Period	Standard error	ΔGDP	ΔCPI	ΔPOP	ΔEC
Variance decomposition for ΔEC					
1	0.1098	0.0000	0.0000	0.0000	100.0000
2	0.1265	6.1647	7.5007	5.2765	81.0579
3	0.1342	7.5470	9.7589	5.4496	77.2444
4	0.5869	28.4666	2.9519	55.6617	12.9196
5	0.7408	25.6139	7.8526	58.1271	8.4065
6	0.7826	31.4098	7.4504	52.2067	8.9329
7	0.8700	38.6859	6.0706	46.8816	8.3618
8	1.4033	37.6689	3.3577	53.1367	5.8366
9	1.5903	35.6902	4.9166	54.8144	4.5787
10	1.7455	41.1086	4.1959	49.4437	5.2517
Variance decomposition for ΔGDP					
1	0.0531	87.9482	0.0000	0.0000	12.0518
2	0.0636	61.2237	4.9431	24.2204	9.6127
3	0.0660	60.3417	5.2980	22.6341	11.7261
4	0.1150	31.7507	2.3520	60.2995	5.5976
5	0.1357	40.5624	4.1662	50.3079	4.9634
6	0.1386	39.9658	4.2816	50.3626	5.3898
7	0.1591	47.6265	4.2349	39.9728	8.1656
8	0.2783	30.5471	3.1056	62.2616	4.0856
9	0.3046	32.1977	5.0798	59.1078	3.6146
10	0.3097	34.2042	4.9159	57.1955	3.6845

EC: Electricity consumption, GDP: Gross domestic product, VECM: Vector-error correction model, CPI: Consumer price index

Table 5: Diagnostic tests for forecast ability

Forecasting diagnostic tests	Dependent variable	
	ΔEC	ΔGDP
Root mean squared error	0.0804	0.1031
Mean absolute error	0.0541	0.0907
Mean absolute percent error	0.6725	0.7027
Theil inequality coefficient	0.0048	0.0040

EC: Electricity consumption, GDP: Gross domestic product

time series technique to the sophisticated econometric models. Consequently, attention was given to the relationship between electricity consumption and income (economic activity), especially on the causality relationship and co-integration relationship between these two variables. Many of empirical studies on these two relationships were conducted based on the VECM framework. However, these studies do not empirically examine the forecasting ability of the VECM in predicting the electricity consumption. Therefore, the objective of this paper is to empirically examine the causality and co-integration relationship between electricity consumption and income based on Malaysian data. On top of that, this paper also investigates the forecasting ability of the estimated model.

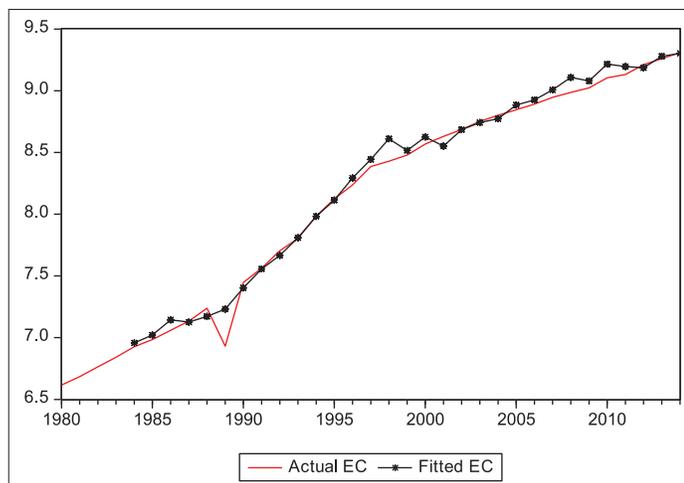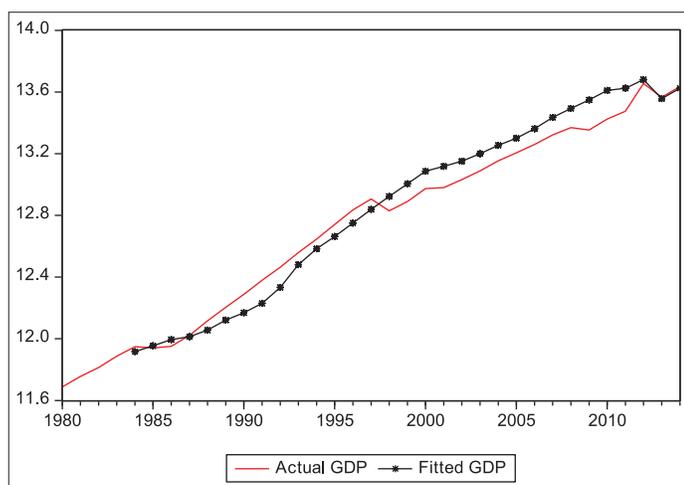**Figure 1:** Plot of actual and fitted value of electricity consumption based on vector-error correction model

Figure 2: Plot of Actual and fitted values of gross domestic product Based on vector-error correction model

The estimation results from co-integration tests indicate that electricity consumption in Malaysia is co-integrated with the level of income, along with two other control variables used in this study: Price level and size of population. The findings suggest the existence of long run relationship between electricity consumption and the level of economic activity, the price level and population in Malaysia. This study finds that the level of income Granger causes electricity consumption. Similarly, the size of population also significantly causes electricity consumption. Empirical evidence also supports the existence of long-run causality that runs from income, price and population size to electricity consumption. The result from causality tests suggest that income and population size are important variables in influencing electricity consumption as well as for the short-run and long-rung forecast of electricity consumption in Malaysia.

The results from variance decompositions analysis show that income explains a considerable percentage of the electricity consumption future variation. Income explains about 25.6% of the total variation in electricity consumption by the end of 5 years, and reaching 41.1% at the end of year 10. Meanwhile,

about 49.4% of the variation in electricity consumption at the end of year 10 can be explained by population size. The results from variance decompositions analysis suggests that both income and population size are important variables in forecasting a variation in electricity consumption. In the final analysis, the forecasting ability of the estimated model was measured through four diagnostic tests: RMSE; MAE; MAPE; and Theil Inequality Coefficient. All diagnostic statistics lead to the conclusion that the electricity consumption regression with income as one of independent variable together with error correction term has better forecasting ability compared with the forecasting ability for income regression.

In conclusion, findings from cointegration tests of this study indicate the existence of long run relationship between income and the level of electricity consumption in Malaysia. The existence of long run relationship between these two variables might implicate that electricity utility is a pre-requisite for economic development of the country. Therefore, it is extremely important for the government to ensure a sufficient supply of electricity power, not only enough for a short term demand but also for the country's long term needs. However, the existence of unidirectional causality running from economy activity to electricity consumption may suggest that the government can implement electricity conservation measures without putting economic development at risk. In this regard, more attention should be given to the alternative source of energy, especially inexpensive and clean energy such as solar energy. Incentives and supportive policies should be introduced in order to encourage general public to fully utilize this energy. Meanwhile, for the electricity supply industry, forecasting demand for electricity consumption is an essential activity and very crucial for power system planning and development. Therefore, the importance of having a good forecasting model needs to be emphasized since the consequences of under or over forecasting are very serious. In this respect, the usage of more sophisticated econometric techniques such as the co-integration approach and the VECM should be considered.

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