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Estimating the Causality and Elasticities of Residential Electricity Consumption for Malaysia

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ABSTRACT

The residential sector is the third-largest electricity user in Malaysia. A clear understanding of the rapid growth in its electricity consumption is crucial to the formulation of energy and environmental policy. This study applied the Autoregressive Distributed Lags, Vector Error Correction Model, and Variance Decomposition Approach in determining the long-run and short-run interaction between electricity consumption by residential sector and the suggested independent variables for 1980-2020 period. The selection of variables is based on the theory of demand. The outcomes confirmed the existence of a long-run relationship among variables. Also, the significant short-run elasticities of residential electricity consumption due to the changes in income and price. However, there is no significant short-run elasticity of residential electricity consumption due to the changes in occupancy and technology. In terms of causality interaction, results show the unidirectional causality running from electricity consumption, income, technology, and occupancy to electricity price in the long run; and the unidirectional causality running from income and occupancy to electricity price in the short run. The bidirectional causality also exists between electricity consumption and electricity price; and technology and electricity price in the short run. The research findings could be beneficial for policymakers in strengthening long-lasting economic policies.

Keywords: Residential Electricity Consumption, Technology Disruption, ARDL, Malaysia
JEL Classifications: O1, O2, Q4, Q5

1. INTRODUCTION

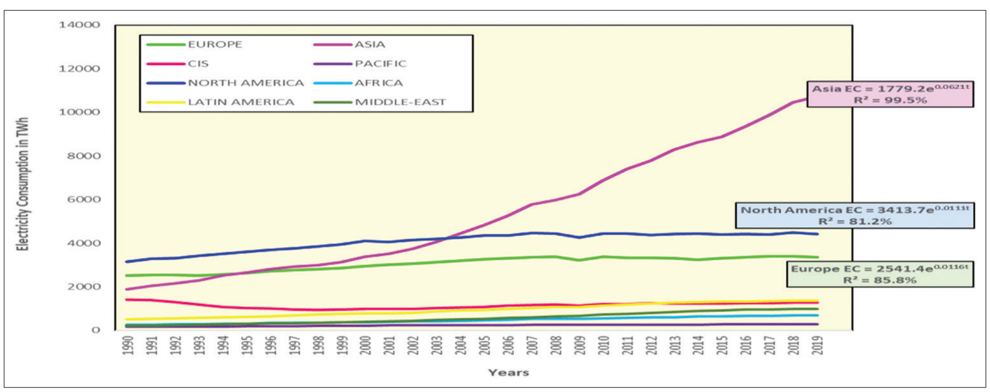
Electricity is globally considered a significant driver of socio-economic activities. The consumption of electricity is one of the major concerns in both developed and developing countries due to its ability to influence the level of environmental and energy sustainability. Instead of socio-economics activities, the number of population or occupancy is one of the major yardsticks to forecast the level of electricity usage. In the modern era, the relationship between population and electricity consumption is common. As the population increases, the number of electrical appliances also increases because the people have to maintain the existing lifestyle and wellness. Therefore, the amount of electricity consumed would increase too. The United Nations Sexual and Reproductive Health Agency (2021) reported that Asia and the Pacific region is home to 60 per cent of the world's population, including the world's most populous countries, China and India. In 2050, the world population is anticipated to skyrocket at 6.5 billion, an increase of 3.5 billion from 2010, with more than half of the world's population living in Asia (4.5 billion), 17% in Africa (1.3 billion), 10% in Europe (742 million), 9% in Latin America and the Caribbean (646 million), and the remaining 6% in Northern America (361 million) and Oceania (41 million) (Ali et al., 2020). The status of the world population distribution is consistent with the electricity consumption database by region, as presented in Figure 1. Asia, with the highest world population, was documented as the largest electricity consumer in the world. In 2019, Asia was recorded with the most influential electricity consumption, followed by North America and Europe.

In line with the world scenario, Malaysia's electricity consumption has shown a steady growth trend with the economic and population growth. As illustrated in Figure 2, electricity consumption grew by 8.1% per year for the 1980-2020 period; the population and GDP growth by 2.3% per year and 6.1 per cent per year for a similar period. As a developing country, Malaysia's total energy consumption is dominated by the industrial, commercial, and residential sector. In comparison, the residential sector is the third-largest electricity consumer (residential accounted 20.5% from total electricity consumption; commercial accounted 30.8% from total electricity consumption; industrial accounted 46% from total electricity consumption) and has the largest number of the consumer of 81.9% from total electricity user (Energy Commission, 2021). Many scholars have confirmed the use of electricity as a cause of environmental pollutions (Salahuddin et al., 2018; Dogan and Ozturk, 2017; Bekhet and Othman, 2017; Ahmad et al., 2017; Dogan and Turkekul, 2016; Begum et al., 2015). The increased consciousness on environmental pollutions, renewed energy (such as solar energy, hydropower energy, wind energy, biomass energy, etc.) and energy efficiency technologies have recharged the interest in residential electricity consumption as compared to other sectors' electricity consumption. Interestingly, the study that observed technology disruption's impact is still limited mainly within the econometric analysis. Hence, there is a need to fill this gap, understand the role of technology disruption on residential electricity consumption and how these indicators interact with each other.

On the other hand, several questions required a solid answer to sketch a solid energy policy for Malaysia. First, in terms of elasticity of electricity consumption. The elasticity measures how the percentage changes in one variable (such as price, income, population, technology, etc.) affect electricity consumption. For instance, understanding how price changes affect electricity consumption allows estimating future generation and capacity requirements (Csereklyei, 2020; Labandeira et al., 2017; Wang and Mogi, 2017) and quantifying changes in welfare effects as a consequence of environmental or energy policy changes (Miller and Alberini, 2016; Burke and Abayasekara, 2018).

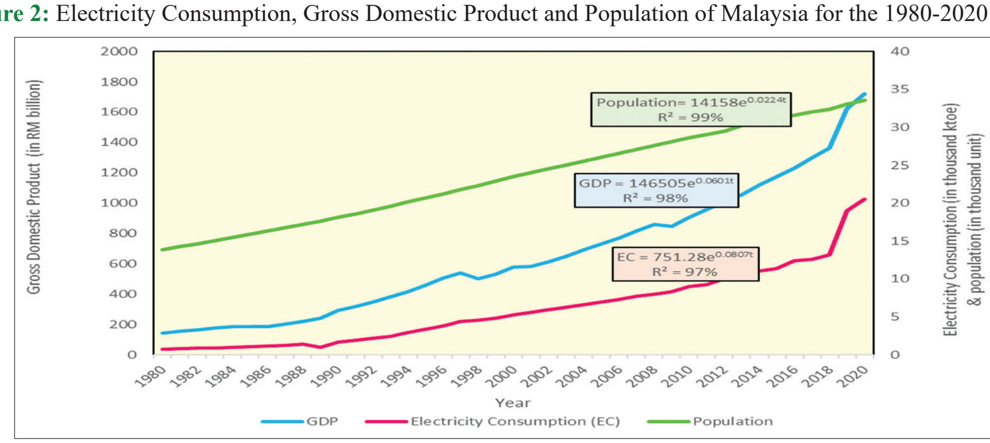
Second, in terms of causality interaction. The direction of causality in Malaysian residential electricity consumption needs further clarification for evaluating the appropriateness of the current policy design and making inferences about the implications of specific programmes or efforts in the electric sector (Abbasi et al., 2021; Tang and Shahbaz, 2013). If Granger causality runs from residential electricity consumption to economic performance, any tool or decision to expand residential electricity consumption may foster economic growth. In this context, the energy conservation policy may not suit Malaysia. However, suppose the Granger causal direction runs from economic performance to electricity consumption; in that case, the electricity conservation policies designed to reduce electricity consumption are less likely to affect the generalised future economic behaviour significantly. A tool or strategy focused on increasing electricity consumption through

Figure 1: Electricity Consumption by Regions



Source: Enerdata Statistical Database 2021 (https://yearbook.enerdata.net/electricity/electricity-domestic-consumption

Figure 2: Electricity Consumption, Gross Domestic Product and Population of Malaysia for the 1980-2020 period



Source: Energy Commission 2021 (https://meih.st.gov.my) economic growth plans may seem adequate to reflect the nature of the said relationship.

Motivated by the abovementioned issues and the enthusiasm to understand Malaysia's situation, this study investigates the residential electricity consumption function with the role of technology disruption. This study utilised the autoregressive distributed lag (ARDL) and Bounds Co-Integration Testing methodology (Pesaran et al., 2001) to estimate the demand equation. The ARDL co-integration approach is widely used in the related literature to estimate both short-run and long-run elasticities of electricity demand concerning price, income, and other factors.

The contribution of this study consists of providing some ideas and policy recommendations on the instruments that could be used to improve economics, the welfare of societies, and the environment via Sustainable Development Goals—2030 (SDG-2030). Besides, the analysis of the results could provide tools and justifications that would help the government strategise the electricity price setting for Malaysian residential sector.

The rest of this study is structured as follows. Section 2 provides a concise review of the past literature. The theoretical framework for modelling residential electricity demand and methodology is elaborated in Section 3. Section 4 discusses the result analysis, and finally, in Section 5, conclusions are drawn, and its implication on energy or environmental policies are presented.

2. CAUSALITY AND ELECTRICITY DEMAND ELASTICITY LITERATURE

The energy—GDP nexus has been widely debated by many scholars in the area of energy and environment economics (Salahuddin et al., 2018; Balaguer and Cantavella, 2018; Ahmad et al., 2017; Xu and Lin, 2017; Ozturk and Al-Mulali, 2015). However, the study on electricity consumption—GDP nexus, mainly for the residential sector, is relatively scant. This section reviews the past studies on the interaction between residential electricity consumption (REC) and GDP, and it would be divided into two categories, i.e. causality interaction and elasticities. Both categories are significant for formulating accurate energy policies; the former is useful in estimating future generation and capacity requirements (Csereklyei, 2020; Labandeira et al., 2017; Wang and Mogi, 2017) and quantifying changes in welfare effects as a consequence of environmental or energy policy changes (Miller and Alberini, 2016; Burke and Abayasekara, 2018). Meanwhile, the latter is a useful tool for evaluating the appropriateness of the policy design or making inferences about the implications of specific programmes or efforts in the electric sector (Abbasi et al., 2021; Tang and Shahbaz, 2013).

Owoeye et al. (2020); Bekhet and Harun (2018); Bildirici and Kayikçi (2016); Acaravci et al. (2015) described the differences in the causality results allow for four hypotheses: (1) the "conservation hypothesis" (supported by the presence of the unidirectional causal relationship moves from GDP to energy consumption); (2) the "growth hypothesis" (supported by the presence of the unidirectional causal relationship moves from energy consumption to GDP); and (3) the "feedback hypothesis" (supported by the presence of the bidirectional causal relationship between GDP and energy consumption) and (4) the "neutrality hypothesis" (supported by the inexistence of causality between GDP and energy consumption. In the first case (conservation hypothesis), the strategy to save energy and the environment is the most appropriate. Any technique to save energy will not adversely affect economic activities and growth. Thus, the suitable policy is to invest in energy efficiency technology, improve the behaviour on energy consumption to support growth, and build a clean and healthy environment. For the second case, via the growth hypothesis, the strategy to conserve energy (energy saving) is inappropriate because it distorts economic activities and growth (Bekhet and Harun, 2018). The best way to ensure a continuous energy supply is by investing in renewable energy (i.e., solar energy, wind energy, biofuel, etc.). For the residential sector, people can install solar PV via Net Energy Metering 3.0 (NEM 3.0), SELCO, battery storage technology, etc. For the third case (feedback hypothesis), the combination of the conversation policy and energy efficiency policy are most appropriate. Finally, for the fourth case (neutrality hypothesis), neither energy conservation policy nor increasing energy policy is workable for those particular countries (Rodríguez-Caballero and Ventosa-Santaulària, 2016). The policymaker needs to encounter other exogenous variables that can directly influence the growth of the countries, such as technology investment. Precisely, several studies have been conducted to estimate the causality relationship and residential electricity consumption, and are summarised in Table 1. The results are inconsistent due to the differences in socio-economic conditions of those particular countries.

Furthermore, the elasticities measure the percentage change in energy or electricity consumption due to percentage change in either price, income, population or other potential determinants. The price elasticity provides an understanding of how price changes affect electricity demand, allows estimating future generation and capacity requirements (Csereklyei, 2020; Labandeira et al., 2017; Wang and Mogi, 2017), as well as plan and organise the adequate supply of electricity to the grids in their respective markets (Cabral et al., 2020). The price elasticity of demand is also a key factor in quantifying changes in welfare effects due to environmental or energy policy changes (Burke and Abayasekara, 2018; Miller and Alberini, 2016). Obtaining valid estimates of elasticities and accurate demand forecasts is crucial to understanding the energy system and the impact of energy policy instruments (Boogen et al., 2017) and have substantial implications for utilities, regulators and policymakers. Theoretically, the price elasticity can be classified from elastic to inelastic (for details, see Ivy-Yap and Bekhet, 2015). The elastic price elasticity indicates that people are sensitive towards the changes in the price of energy or electricity because energy or electricity for them is a normal good, people have longer or enough time to alter their consumption and respond to the price changes, or there are other alternatives to substitute the role of energy or electricity. However, inelastic price elasticity specifies that people are not sensitive towards the price change, or they have limited time to alter their consumption or the role of energy or electricity as a necessity good or lack of substitute goods and

Table 1: Selected literature on causality and residential electricity demand elasticity

Authors	Countries	Methodology	Results on elasticities	Results on causality
Narayan and Smyth (2005)	Australia	Bound Testing	Income elasticity = inelastic Price elasticity = inelastic	
Dergiades and Tsoulfidis (2008)	USA	ARDL	Income elasticity = inelastic Price elasticity = elastic	Long run: Y → REC (conservation hypothesis) P → REC (conservation hypothesis)
Dergiades and Tsoulfidis (2009)	Greece	ARDL	Income elasticity = inelastic Price elasticity = inelastic	Long run: Y → REC (conservation hypothesis) P → REC (conservation hypothesis)
Lang et al. (2010)	Taiwan	GC		EC → Y REC → Y (neutrality hypothesis)
Ivy-Yap and Bekhet (2015)	Malaysia	ARDL	Income elasticity = elastic Price elasticity = inelastic	
Ivy-Yap and Bekhet (2016)	Malaysia	ARDL		Long run: Po → REC (conservation hypothesis) REC → P (feedback hypothesis) Y → REC (conservation hypothesis) Short run: Po → REC (conservation hypothesis) REC → P
Bildirici and Kayikci (2016)	Eastern Europe	ARDL	Long run: Income elasticity = elastic Price elasticity = elastic Short run: Income elasticity = inelastic Price elasticity = inelastic	Y → REC (conservation hypothesis)
Cabral et al. (2020)	Brazil	Spatiotemporal model	Income elasticity = inelastic Price elasticity = inelastic	
Csereklyei (2020)	European Union	GMM	Price elasticity = inelastic	
Abbasi et al. (2021)	Pakistan	J.J VECM		REC → Y (growth hypothesis)
Bohlmann and Inglesi-Lotz (2021)	South Africa		Income elasticity = inelastic Price elasticity = inelastic	

REC = Residential Electricity Consumption; P = Price / Tariff; Po = Population; Unidirectional Causality; Bidirectional Causality

alternatives to replace the function of energy or electricity (Cabral et al., 2020). For inelastic demand, reducing consumption would not be effective by increasing the tariff, ceteris paribus vice versa. The same goes for the concept of income elasticity. If the income elasticity is elastic, the energy or electricity is classified as a normal or luxury good. On the other hand, if the income elasticity is inelastic, it indicates the energy or elasticity as a necessity good. The selected past literature on causality and residential electricity demand elasticity is presented in Table 1.

Instead of the abovementioned issues, recently, technology disruption has played a significant role in determining residential electricity consumption. The impact of technological disruption on economic growth can be traced to the pioneering work of growth theorists during the second half of the twentieth century (Solow, 1956; Romer, 1986), and it significantly influenced the long-run growth. However, studies on electricity usage and technological disruption have yielded some interesting results from the energy literature review. For instance, Tang and Tan (2013) investigated the effect of technological disruption, energy prices and economic growth on electricity consumption in Malaysia. Technological disruption and energy prices were proxied by the number of patents registered and the consumer price index, respectively. It was found that technological innovation and energy prices negatively affected electricity consumption. Murad et al. (2019) examined the relationships among energy consumption, energy price, economic growth and technological innovation in Denmark. Based on the ARDL methodology, a significant negative relationship between technological innovation and energy consumption was obtained. Fei and Rasiah (2014) examined the long-run and short-run relationship among electricity consumption, economic growth, energy prices and technological innovation for Canada, Ecuador, Norway and South Africa using ARDL and VECM techniques. The result revealed an insignificant effect of technological innovation on electricity consumption. Ivy-Yap and Bekhet (2015) measured the impact of technology (represented by FDI) on residential electricity consumption and revealed the existence of a negative impact on residential electricity consumption.

Past literature shows that the interaction between residential electricity consumption, electricity price, income, and technology is still in the infant stage. So far, only the study by Ivy-Yap and Bekhet (2015) is quite close to the current study. But unfortunately, the uniqueness of the current study holds with the intention to estimate the dynamic interaction (long-run and short-run causality and elasticities) between residential electricity consumption and its determinants by considering the role of technology disruption proxy by renewable energy.

Accordingly, this study hypothesis the following for the case of Malaysia:

- H_1: Significant long-run relationship among residential electricity consumption, electricity price, technology disruption, and other potential determinants
- H_2: Significant long-run and short-run elasticities of residential electricity consumption due to the changes in its potential determinants
- H_3: Significant long-run and short-run causality relationship between residential electricity consumption and its potential determinants.

3. THEORETICAL FRAMEWORK AND ESTIMATION PROCEDURE

This section is divided into two subsections. The first one presents the theoretical framework for modelling residential electricity consumption and the source of data. The second comprises estimation procedure via the stationary and co-integration tests, robustness checking, and causality relationship.

3.1. Theoretical Framework for Modelling Residential Electricity Demand and Source of Data

One of the major constraints of the policymaker is to estimate electricity demand with incomplete information in hand (Labandeira et al., 2012). Therefore, developing a well-specified electricity demand model is a must. Through it, policymakers can model the electricity demand of their markets and guarantee productive, allocative and environmental efficiencies (Cabral et al., 2020).

The development of the residential electricity consumption (REC) framework is adapted from the demand theory (Tang and Tan, 2013). The REC is related to income (Y), electricity prices (P) and population (Po), and the relationship with REC is anticipated to be positive, negative and positive, respectively. Therefore, the theoretical electricity consumption function can be written as follows:

$$REC_t = f(Y_t, P_t, Po_t) \quad [1]$$

In line with the aim of this study which is to measure the impact of technology disruption on REC, the new theoretical framework is presented as Equation [2].

$$REC_t = f(Y_t, P_t, Po_t, T_t) \quad [2]$$

Where the T_t is representing technology. Notably, the main issue in developing the REC empirical model is in terms of data availability. The observation period (t) should be large enough to consider more exogenous variables, or it would reduce the degree of freedom. To cater to that particular problem, all the unmentioned variables will be placed on the error term (ε_t). Hence, the REC's empirical model is presented in the form of ordinary least squares (OLS) as Equation [3].

$$LREC_t = \alpha_0 + \alpha_1 LY_t + \alpha_2 LP_t + \alpha_3 LPo_t + \alpha_4 LT_t + \varepsilon_t \quad [3]$$

In Equation [3], the L represents the natural logarithm[1], the $LREC_t$, LY_t, LP_t, LPo_t, and LT_t denote residential electricity consumption, income per capita, electricity price, occupancy (population), and technology, respectively. Meanwhile, the $\alpha_{i,\,[i=1,2,3,4]}$ indicates the coefficient of elasticity of residential electricity consumption due to the changes in income, price, occupancy, and technology, respectively. The error term ε_t is assumed to be normally distributed and of white noise.

This study uses secondary data of residential electricity consumption, per capita real GDP, electricity prices (proxy by an energy price index), occupancy (proxy by the number of population) and technology renewable (proxy by renewable energy production). All data were extracted from the Malaysia Energy Information Hub (MEIH) (2021) and the Department of Statistics Malaysia (DOSM, 2020).

3.2. Estimation Procedure

3.2.1. Stationary and co-integration tests

Before examining the association between REC and its determinants, it is important to check whether the series is stationary. Many unit root tests are available to investigate the stationarity of the series, and this step is considered important to avoid spurious regression results and spoil the overall research outcome. In this paper, the augmented Dickey-Fuller (ADF) and Philips-Perron (PP) is utilised for that particular purpose before embarking on OLS. According to Shahbaz et al. (2013), this test is suitable for a small sample size with no structural break. Further, the stationarity test can provide the researcher with an idea of what model to use in the future and detect a shock or structural break in the time series (Bekhet and Othman, 2017; 2018).

Next, the F-bounds co-integration test was used to search for a long-term relationship between the study variables. This technique is progressing well in addressing some of the shortcomings of the more traditional co-integration techniques (i.e. Engle and Granger, 1987, test; Johansen and Juselius, 1990, test). These shortcomings include strict requirements for all variables to be I(1), less efficiency with the inclusion of dummy variables (Ahmad et al., 2017; Pesaran et al., 2001) and the strict condition of large sample asymptotic. In this regard, Pesaran et al. (2001) mentioned that ARDL performs better than Johansen co-integration for the case of a small sample size

1 All variables will be transformed to natural logarithm to induce stationarity in the variance–covariance matrix (Tan & Tang, 2013).

(estimated 30 to 80 observations). In addition, Narayan (2005) highlights two additional advantages of ARDL: the ability to avoid endogeneity and serial correlation problHems; second, variables for inclusion in the modelling can be a combination of stationary and nonstationary levels. Hence, the dynamic relationship among REC and their elements can be measured as in Equation [4]:

$$\Delta LREC = \beta_0 + \beta_1 LREC_{t-1} + \beta_2 LY_{t-1} + \beta_3 LPo_{t-1} + \beta_4 \ln T_{t-1} + \sum_{j=0}^{k} \Delta\theta_1 LREC_{t-j} + \sum_{j=1}^{k} \Delta\theta_2 LY_{t-j} + \sum_{j=1}^{k} \Delta\theta_3 LPo_{t-j} + \sum_{j=1}^{k} \Delta\theta_4 LT_{t-j} + \varepsilon \quad [4]$$

Equation [4] is the unrestricted ARDL model specified as conditional error correction model (ECM) with β_1 $LREC_{t-1}$ + β_2 LY_{t-1} + β_3 LPo_{t-1} + β_4 $\ln T_{t-1}$ replacing the error correction term (μECT_{t-1}) of a standard ECM. Then, Δ is the presenting of the first difference operator, β_0 represents the intercept, β_{1-5} denotes the long-run elasticities of the variables, and θ_{1-5} represents the short-run elasticities of the variables. $\mathcal{E}$ represents the error term, k is the maximum lag length, and j indicates the lag's optimal number, and this study uses the Akaike information criterion (AIC). The AIC tends to select the maximum relevant lag length, increase the model's dynamic, and avoid under-fitting the model (Zhang et al., 2021; Bekhet and Othman, 2017).

To assess whether the variables are co-integrated (have a long-run relationship), the F-test was conducted. The hypotheses are formulated as follows:

H_0: $\beta_{1-5} = 0$ (no co-integrated) against

H_1: $\beta_{1-5} \neq 0$ (co-integrated exist).

Similarly, the computed F-statistic is assessed using the critical values introduced by Pesaran et al. (2001). These critical values are of two types: lower bound critical values and upper bound values. The former expects all the variables to be I(0), while the latter assumes all variables to be I(1). The condition is as follows: H_0 for no co-integration relationship will be rejected if F-statistics value > I (1) critical value; H_0 for no co-integration relationship will be not rejected if F-statistics < I(0) critical value; and finally, the result is inconclusive if the value of F-statistics falls in between I(0) and I(1) critical value (Abbasi et al., 2021; Zhang et al., 2021; Bekhet and Othman, 2017; Pesaran et al., 2001). According to Tursoy and Faisal (2018), when the bounds test result is inconclusive, the result of the error correction term (ECT) can be used in deciding whether there is a long-run relationship among the variables of interest. Thus, if the coefficient of the ECT, as shown in the short-run ECM (Equation 5), is negative and statistically significant, we conclude that the long-run relation does exist (Kremers et al., 1992; Banerjee et al., 1998). Likewise, the long-run elasticities can be measured using the level OLS model, as shown in Equation [3]. To estimate the short-run elasticities, a dynamic ECM would be estimated. The ARDL specification of the ECM is presented as follows:

$$\Delta LREC = \beta_0 + \sum_{j=0}^{k} \Delta\theta_1 LREC_{t-j} + \sum_{j=1}^{k} \Delta\theta_2 LY_{t-j} + \sum_{j=1}^{k} \Delta\theta_3 LP_{t-j} + \sum_{j=1}^{k} \Delta\theta_4 LPo_{t-j} + \sum_{j=1}^{k} \Delta\theta_5 LT_{t-j} + \delta ECT_{t-1} + \varepsilon \quad [5]$$

Here, δ is the coefficient of the error correction term indicating the speed at which the variables meet at the equilibrium position. Later, the $\mathcal{E}_t$ terms should be diagnosed, and they typically are distributed with zero mean and constant variance, $\mathcal{E}_t \sim N(0,\sigma_2)$, homoscedastic, free from autocorrelation problems, and have no multicollinearity. The model considers bias in the parameters inefficient and the outcome from the hypothesis invalid if the above criteria are not met. Then the Arch, Breusch–Godfrey, Breusch–Pagan–Godfrey, and RAMSEY tests are employed to ensure that the estimated model is free from the abovementioned problems and is reliable (Abbasi et al., 2021).

Further, the model's stability would be measured by utilising the CUSUM and CUSUMQ tests (Brown et al., 1975). In a condition where the CUSUM and CUSUMQ plots are placed inside the 5% significance level, the model is considered stable (Bekhet and Matar, 2013). Otherwise, the model is considered unstable with the existence of structural break within the estimation period (Abid, 2015).

3.2.2. Robustness checking

Further, this study utilises the dynamic ordinary least squares (DOLS) and fully modified dynamic ordinary least squares (FMOLS) tests developed by Stock and Watson (1993) for robustness check. These models contain both leads and lags of the exogenous variables. Instead, its ability to control the endogeneity and serial correlation can provide consistent estimates in the case of a small sample size (n is up to 60) and make it superior to OLS (Akram et al., 2019).

3.2.3. Causality relationship

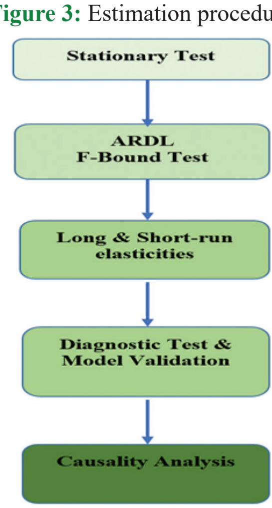
The presence of a long-run relationship is a sign of at least a one-way relationship among the variables. The ARDL approach examines the presence or absence of co-integration between the variables, but it does not test the direction of causality. Remarkably, causality information is essential for policymakers to recognise the variables' causality directions to regulate suitable policies. This study uses the VECM Granger causality approach to examine the causal relations of a two-step process of Engle and Granger (1987). The first step estimates the long-run elasticities in Equation [3] to obtain the residuals (ECT) corresponding to the deviation from equilibrium. The second step estimates the elasticities related to the short-run adjustment. The resulting equations are used in conjunction with the Granger causality testing as presented in Equation [6]:

$$\Delta\begin{bmatrix} LREC \\ LY \\ LP \\ LPo \\ LT \end{bmatrix}_t = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \\ \varphi_5 \end{bmatrix} + \sum_{j-1}^{m}\Delta\begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{35} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} & \beta_{45} \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & \beta_{55} \end{bmatrix}_j \begin{bmatrix} LREC \\ LY \\ LP \\ LPo \\ LT \end{bmatrix}_{t-j} + \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \end{bmatrix}\begin{bmatrix} ECT_1 \\ ECT_2 \\ ECT_3 \\ ECT_4 \\ ECT_5 \end{bmatrix}_{t-1} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix}_t \quad (6)$$

Where ϕ_i (i = 1-5) represents the constant, j (j = 1,...,m) is the optimal lag length determined by the minimisation of AIC criterion, ECT_{t-1} is the estimated lagged error correction term derived from the long-run relationship presented in Equation [3] and estimated via Equation [6], γ_i (i = 1-5) is the speed of adjustment coefficient. The t-test is utilised to measure the significance of the long-run causality relationship represented by the coefficient ($_{is}$) of ECT_{t-1}(Ivy-Yap and Bekhet, 2016). Instead, the Wald F or χ^2 test is utilised to determine the existence of the short-run causality relationship represented by the coefficients ($\beta_{i,js}$) for each explanatory variable. However, the ε_i (i = 1-5) is the disturbance term assumed to be uncorrelated with zero means. Unlike Equation [5], all error-correction vectors in Equation [6] are estimated with the same lag structure (m), which is determined in the unrestricted VAR framework. Figure 3 summarises the estimation procedure utilised in this study.

The previous estimation techniques do not illustrate the complete story about the interactions between the variables of a system and do not guarantee the credibility of the causality relationship (Bekhet and Othman, 2018). Its role played around the observation period, which is from 1980 to 2020. However, to the measurement of the importance of causality among the variables beyond the sample period (Onafowora and Owoye, 2014; Shahbaz et al., 2014), the Variance Decomposition Approach (VDA) within a VAR framework will be employed (Ivy-Yap and Bekhet, 2016; Pesaran et al., 2001). The VDA demonstrates how much of the variance in the dependent variable's forecast error may be explained by exogenous shocks to the independent variables. The bigger the percentage of the dependent variable's forecast error variance, the more important the causal impact of the independent variable on the dependent variable is, and vice versa (Alshehry and Belloumi, 2017). Likewise, the VDA demonstrates and checks out the credibility of the direction of causality relationship among variables.

Figure 3: Estimation procedure



4. RESULT ANALYSIS

This study utilised two-unit root tests such as augmented Dickey-Fuller (ADF) of Dickey and Fuller (1979) and Phillips-Perron (PP) of Phillips and Perron (1988) to check the unit root properties of the variables. The results indicate that all series (except for LPo) contain unit root problems at their levels but are found to be stationary at first difference [I(1)]. Unfortunately, the LPo is found stationary at level [I(0)]. The results are summarised in Table 2.

The first step in applying the ARDL bounds testing approach to co-integration is the selection of optimal lag length. The appropriate lag length of 4 (Appendix A) is selected based on the minimisation of AIC; it is sufficiently long for annual data, i.e., 1980-2020, to capture the dynamic relationship of the ARDL model. The AIC statistic is used because it has superior properties, particularly in a small sample (Lütkepohl, 2005). Table 3 presents the results of the F-Bounds test. The empirical findings show long-run relationships between all variables at a 1% significant level over the 1980-2020 period, and it is consistent with Bildirici and Kayikci (2016); Ivy-Yap and Bekhet (2016); and Dergiades and Tsoulfidis (2008; 2009). This is because the calculated F-statistic for each model is higher than the upper bound critical value at a 1% significance level.

The stability of this model can be captured through its error terms via diagnostic tests (Table 3). The result shows the Jarque–Bera (JB) normality test cannot reject the null hypothesis of normality, implying that the error terms are normally distributed. Therefore, the standard R-squared, t-statistics and F-statistics can be used for statistical inferences

Table 2: Unit root tests results

Variables	ADF	PP	Conclusion
LREC			
I(0)	−1.249	−1.185	I(1)
I(1)	−5.765[a]	−5.829[a]	
LY			
I(0)	−0.066	−0.066446	I(1)
I(1)	−5.588[a]	−5.585424[a]	
LP			
I(0)	−0.911	−2.420154	I(1)
I(1)	−3.239[b]	−3.239715[b]	
LPo			
I(0)	1.579	−6.089181[a]	I(0)
I(1)	−1.897	−6.089181	
LT			
I(0)	−0.775	−0.692150	I(1)
I(1)	−0.775[a]	−5.224755[a]	

ADF and PP critical value: 1% (-3.610); 5%=-2.2939; 10%=-2.608; and a,b,c=significant at 1%; 5% and 10%. respectively

(Tang and Tan, 2013). Furthermore, the Breusch–Godfrey LM test for serial correlation and the Autoregressive Conditional Heteroscedasticity (ARCH) LM test consistently suggest that the error term is free from serial correlation and heteroscedasticity problems. Moreover, the model is also correctly specified because the Ramsey RESET test cannot reject the null hypothesis of no general specification error at the 1% significance level. The CUSUM and CUSUM of squares statistics plots also fluctuate within the 5% critical bounds (Figure 4). Therefore, the estimated coefficients are stable over the sample period from 1980 to 2020.

After confirming the existence of a co-integration relationship among variables in the REC model, the next step is to measure the long-run and short-run elasticities. Table 4 summarises the long-run elasticities and the short-run elasticities. Specifically,

Figure 4: CUSUM and CUSUMSQ

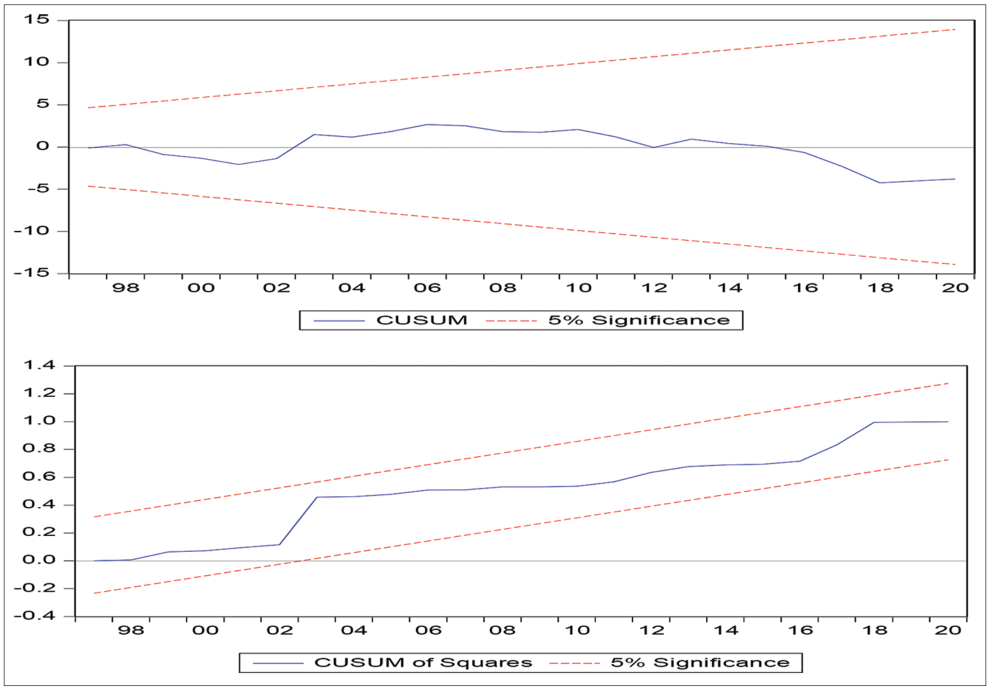


Table 3: Result of F-bounds test and residual diagnostic checking

Model	F-Stat.	Critical Value			Decision
		Level	I(0)	I(1)	
LREC/ LY,LP,LPo,LT	6.054[a]	10%	2.427	3.395	Co-integrated
		5%	2.893	4.000	
		1%	3.967	5.455	

Test	F-Stat/Probability	Decision
Normality test	6.981 (0.030)[a]	$H_{0:}$ Normal distributed
Breusch-Godfrey Serial correlation test	1.182 (0.325)[b]	H_0: No serial correlation
ARCH-Heteroscedasticity test	0.209 (0.650)[b]	H_0: No Heteroscedasticity
Ramsey RESET test	0.050 (0.824)[b]	H_0: Model has a correct functional form

Source: Output of EVIEWS package version 10. [a,b,c]defined in Table 3

Table 4: Long-run and short-run elasticities

Level Equation, Case 2: Restricted Constant and No Trend							
Long - Run				Short - Run			
Variables	Coefficient	t-Statistic	Prob.	Variables	Coefficient	t-Statistic	Prob.
LY	0.377	1.425	0.166	ΔLY	−0.017	−0.166	0.868
LP	0.712	0.914	0.369	ΔLY_{t-1}	−0.123	−0.995	0.329
LPo	2.290[b]	2.298	0.019	ΔLY_{t-2}	−0.097	−0.817	0.421
LT	−0.157[a]	−4.240	0.000	ΔLY	−0.456[a]	−3.741	0.001
C	−21.792[a]	−4.713	0.000	ΔLP	0.236	0.397	0.694
				ΔLP	−1.760[c]	−2.035	0.053
				ΔLP	2.415[a]	4.153	0.000
				ECT	−0.588[a]	−6.625	0.000

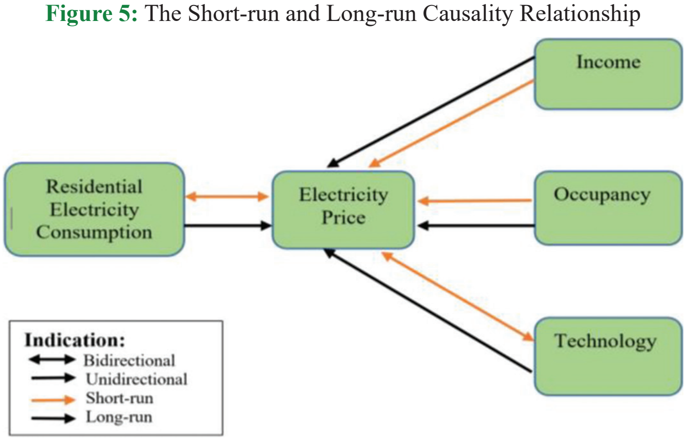
[a,b,c]defined in Table 3. ECTt-1 = LREC – (0.377*LY +0.712*LP + 2.290*LPo -0.157*LT – 21.792)

it shows the elasticity of REC as a result of the changes in occupancy is elastic where the 1% increase in occupancy will increase the electricity consumption by 2.29%, ceteris paribus at a 5% significance level. The elasticity of REC as a result of the changes in technology is inelastic (with a negative sign). This means the 1% increase in technology will reduce the electricity consumption by 0.15%, ceteris paribus at a 1% significant level. Therefore, increases in technology disruption play an important role in reducing the REC, and the higher the number of occupancies, the higher the amount of REC. However, the elasticity of REC due to the changes in income and price is not significant in the long run.

Conversely, there are significant short-run elasticities of REC due to the changes in income (inelastic) and price (elastic) in the short run. The result of income elasticity is consistent with Bohlmann and Inglesi-Lotz (2021), Cabral et al. (2020), and Bildirici and Kayikci (2016) but inconsistent with Ivy-Yap and Bekhet (2015). However, the result of price elasticity is consistent with Dergiades and Tsoulfidis (2008) for the case of the USA and inconsistent with Narayan and Smyth (2005), Dergiades and Tsoulfidis (2009), and Bildirici and Kayikci (2016). Instead, no significant short-run elasticity of residential electricity consumption due to the changes in occupancy and technology in the short run are found. This result means that electricity is a necessity good (basic requirement) for Malaysian people. Electricity is vital no matter whether their income increases or decreases, and they have to maintain a certain level of usage to support their current lifestyle and necessities. Also, this study reveals the increase or decrease in electricity price is only a short-term issue for Malaysian people. People tend to adjust their consumption in the short term but not in the long term. However, the long run comes with a different story. In the long run, the electricity usage pattern depends on the level of occupancy and the level of technologies employed. The above results are consistent with other methods (DOLS and FMOLS) and it is reported in Appendix B.

At the same time, the results indicate the disequilibrium in the short run has been adjusted by 58.8% per year towards long-run equilibrium. The full convergence process to its equilibrium takes after 1.7 years (1 year and 4 months). Thus, the speed of adjustment is significantly fast in the case of any shock or innovation to the residential electricity demand equation or model.

Figure 5: The Short-run and Long-run Causality Relationship



Source: Refer to Appendix C

Because the variables are co-integrated, the Granger causality test results are presented in the VECM framework. The direction of causality can be divided into short-and-long runs of causation. The short-run causality is determined by the statistical significance of the partial F-statistics associated with the right-hand side variables. The long-run causality is revealed by the statistical significance of the respective error correction terms using a t-test. The results suggest the electricity price as an endogenous solid. This is because most of the variables show a causal direction to electricity price. In specific, it can be presented as follow: (1) The unidirectional causality running from electricity consumption, income, technology, and occupancy to electricity price in the long run; (2) The unidirectional causality running from the income and the occupancy to the electricity price in the short run; (3) The bidirectional causality between the electricity consumption and the price; and the technology and the price in the short run. The details are presented in Figure 5.

The purpose of the VDA is to measure the percentage change in an endogenous variable if there is a change or shock, or innovation in exogenous variables. Likewise, it can measure the major contributor to the changes in the endogenous variable. Table 5 shows initially, 100% of changes in REC are because of its own shock. In year 10, 17.3% of changes in EC are because of changes in income, 14% changes in REC are because of changes in occupancy, and 12% changes in REC are because of changes in technology. However, in 20 years' duration, almost 40% changes in REC is because of income and technology (20.7%: income and 19.3%: technology). In sum, this study reveals that income and technology are the major factors that influence electricity consumption pattern in the residential sector in the

Table 5: Variance decomposition approach

Variance decomposition approach of REC						
Period	S.E	LREC	LY	LP	LPo	LT
1	0.0467	100.00	0.00	0.00	0.00	0.00
2	0.0700	78.62	8.42	1.32	4.57	7.05
3	0.0892	65.98	15.32	1.26	9.21	8.20
4	0.1139	64.32	14.29	1.25	13.89	6.22
5	0.1394	60.36	15.48	0.83	17.13	6.17
6	0.1636	57.19	16.64	0.64	19.15	6.35
7	0.1881	56.89	16.40	0.92	19.23	6.53
8	0.2130	55.66	16.55	2.09	17.93	7.75
9	0.2369	53.80	17.00	3.53	15.97	9.67
10	0.2603	52.05	17.29	4.95	13.83	11.86
11	0.2829	49.96	17.70	6.11	11.92	14.28
12	0.3030	48.04	18.26	6.76	10.46	16.46
13	0.3198	46.72	18.77	7.00	9.42	18.06
14	0.3334	45.88	19.27	7.01	8.71	19.10
15	0.3439	45.44	19.73	6.90	8.26	19.64
16	0.3521	45.33	20.07	6.76	8.02	19.80
17	0.3586	45.36	20.31	6.65	7.91	19.74
18	0.3642	45.44	20.48	6.57	7.88	19.60
19	0.3692	45.53	20.59	6.54	7.86	19.45
20	0.3739	45.58	20.67	6.56	7.82	19.34

Cholesky Ordering: LREC LY LP LPo LT

future (20 years). This outcome is consistent with Zakaria and Shamsuddin (2016).

5. CONCLUSION AND POLICY IMPLICATIONS

This study attempts to examine the residential electricity consumption model for Malaysia. Annual data from the 1980 to 2020 period is used. The uniqueness of this study holds by the inclusion of technology disruption in the model. The residential sector is the third-largest electricity user in Malaysia. A clear understanding of the rapid growth in its electricity consumption is crucial to the formulation of energy and environmental policy. This study applied the dynamic model via ARDL, VECM Granger causality, and VDA to determine the long-run and short-run interaction between electricity consumption by the residential sector and the suggested exogenous variables for the 1980-2020 period. The selection of variables is based on the theory of demand. The results of this study confirmed the existence of a long-run relationship among variables. In addition, the significant short-run elasticities of residential electricity consumption due to the changes in income and price in the short-run. However, there was no significant short-run elasticity of residential electricity consumption due to the changes in occupancy and technology in the short run. In terms of causality interaction, results show the unidirectional causality running from electricity consumption, income, technology, and occupancy to electricity price in the long run; and the unidirectional causality running from income and occupancy to electricity price in the short run. The bidirectional causality also exists between electricity consumption and electricity price; and technology and electricity price in the short run. The research findings could be beneficial for policymakers in strengthening long-lasting economic policies.

Based on the results above and Malaysia's Sustainable Development Goals (SDG) in the year 2030, this study highlights some points related to policy implications. In the short run, policymakers need to consider the role of pricing (electricity tariff) to control electricity usage. The condition is quite controversial because, on the one hand, an increased price or tariff will reduce the electricity consumption by the residential sector and improve the revenue of the electricity provider. On the other hand, the opportunity cost is the social-economic and welfare of the society. This is because the price or tariff increase will reduce people's purchasing power and reduce their disposable income[2]. Since the electricity price or tariff is the endogenous solid, the price or tariff setting can be based on level of electricity usage (second-degree price discrimination), income level, i.e., B40, M40 or T20[3] (third-degree price discrimination), according to peak or non-peak hour of electricity usage (peak load pricing), or according to the amount of occupancy. Besides, the price-setting can be discriminated according to the kind of technology employed by the residential sector or the source of technology. The kind of technology associated with the residential sector is solar PV, battery storage, smart meter, electricity charger, and energy-efficient household appliances. In this case, price discrimination can be applied by charging a different product price to a different consumer. Some consumers will be charged at cost optimum (MR=MC), some consumers will be charged above the optimum level, and some customers will be charged below the optimum level. The consumer can be grouped either according to electricity usage or according to income distribution or according to peak hour usage, or according to the technology employed. Furthermore, this study estimates the role of income and technology use will remain important in the long run and the future. This study can be extended by investigating consumer behaviour towards electricity consumption. By understanding consumer behaviour, the regulator can formulate fruitful policy implications in line with SDG 2030.

2 23.6% of income was allocated for water, electricity, and fuel expenditures (Department of Statistics Malaysia, 2019).

3 Income distribution group for Malaysia: B40: ≤ RM4849; M40: RM4850-RM10959; T20: >RM15039 (Department of Statistics Malaysia, 2019).

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APPENDIX TABLES

Appendix A: VAR lag order selection criteria

Endogenous variables: LREC LY LP LPo LT						
Exogenous variables: C						
Date: 04/17/21 Time: 15:32						
Sample: 1980 2020						
Included observations: 37						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	166.1543	NA	1.13e-10	−8.711044	−8.493353	−8.634298
1	429.8583	441.8824	2.86e-16	−21.61396	−20.30781*	−21.15349
2	471.5514	58.59573*	1.26e-16	−22.51629	−20.12169	−21.67208
3	501.9055	34.45591	1.16e-16	−22.80570	−19.32264	−21.57776
4	540.5268	33.40221	8.81e-17*	−23.54199*	−18.97046	−21.93031*

*Indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

Appendix B: Robustness analysis for the long run elasticities

Variables	Co-integrating Regression			
	OLS	DOLS	FMOL	CCR
Income	+ve	+ve	+ve	+ve
Price	+ve	+ve	+ve	+ve
Occupancy	+ve	+ve	+ve	+ve
Technology	−ve	−ve	−ve	−ve

The result is consistent among 4 types of regression models

Appendix C: VECM granger causality result

Models	Chi-square statistic					ECT_{t-1}	t-statistic
	ΔLREC	ΔLY	ΔLP	ΔLPo	ΔLT		
ΔLREC	-	4.652	11.933[a]	2.783	4.598	0.084	0.586
ΔLY	2.087	-	3.032	1.773	1.846	0.177	1.133
ΔLP	48.732[a]	23.074	-	79.736	38.454[a]	0.108[a]	7.036
ΔLPo	1.847	2.030	0.604	-	4.114	-0.002	−0.452
ΔLT	6.079	0.599	11.437	3.815	-	0.869	1.691

Source: Output of Eviews 10