The Philippine Review of Economics
57(1): 121-151. DOI: 10.37907/6ERP0202J

Forecasting residential electricity demand in the Philippines using an error correction model

Angelo Gabrielle Santos*
George Mason University

This study uses an Error Correction Model (ECM) to forecast residential electricity demand in the Philippines using household final consumption expenditure, residential electricity price, and temperature as explanatory variables. Results show that there is a long-run relationship between household final consumption expenditure and residential electricity demand. Estimates from the ECM are consistent with economic theory, and the model passed standard diagnostic and parameter stability tests. Forecast performance based on within-sample and out-of-sample forecasts of the ECM is also shown to be superior, relative to a benchmark Autoregressive Distributed Lag (ARDL) model. Simulations show that by 2040, residential electricity consumption will range from 42,500 gigawatthours (GWh) based on a weak income growth scenario and 62,000 GWh based on a combined changes scenario.

JEL classification: C22, C53, Q47
Keywords: electricity consumption, forecasting, error correction model

1. Introduction

Philippine households face the highest electricity cost in the Southeast Asian region [Ravago et al. 2016]. Policy discussion has focused on how prices can be brought down over time. Increasing generation capacity, especially those of low-cost fuel sources, is among the widely discussed proposal, but this approach must be pursued with demand targets in mind to ensure the right amount of investments in generation capacity. At the same time, meeting the emission targets must also be considered in decisions concerning the expansion of generation capacity especially that low-cost fuels tend to emit larger amounts of greenhouse gases. With all these considerations, long-run projections of total electricity consumption are critical to making the best policy choices to ensure reliable, consistent, and clean use of electricity. This paper contributes to the policy dialogue on

* Address all correspondence to giof.santos11@gmail.com.

generation capacity expansion by analyzing the relationships between key aggregate indicators with household electricity consumption using cointegration techniques, and by forecasting the growth of household electricity demand in the near future based on the estimated short- and long-run elasticities. It extends the work of Danao and Ducanes [2016] who used the same cointegration technique but forecasted aggregate electricity consumption rather than the consumption of a specific customer class as done in this paper.

Forecasting aggregate electricity demand would more directly guide policy discussion on generation capacity and fuel mix. However, forecasts based on aggregated heterogeneous goods strongly assume similarity in determinants and size of elasticities among specific components. In forecasting aggregate electricity demand, this is a practical concern, especially in estimating the elasticities of climactic variables. For instance, Alabbas & Nyangon [2016] found that in responsiveness to weather changes, industrial customers are not as sensitive as residential customers. By analyzing the behavior of a specific customer class, a more appropriate set of predictors can be used and ultimately, result in better forecasting performance.

This paper has two goals: first, to estimate how residential electricity consumption responds to changes in household income, prices, and temperature using an error correction model (ECM); and second, to use these estimates to forecast residential electricity demand growth under various economic and climatic scenarios. Two time-series models were compared in terms of prediction error: a simple Autoregressive Distributed Lag Model (ARDL) and an ECM. Both models stood to have relatively low forecast errors despite the limited sample size. But the ECM has a superior forecasting performance and thus, it is used to forecast long-run residential electricity demand growth under varying assumptions.

Estimates using the ECM show that residential electricity demand is influenced by short-run price and temperature changes. Household income, proxied by real household final consumption expenditure, is found to be insignificant in the short run, but a cointegration test suggests that it has a long-run equilibrium relationship with residential electricity demand. Based on the simulations, residential electricity consumption will range from 42,500 gigawatt hours (GWh) to 61,942 GWh by 2040 depending on the scenarios assumed.

This paper is organized as follows: Section 3 describes how residential electricity demand changed over time using data reported by the Department of Energy. Section 3 discusses the movement of household electricity demand and its predictors over time. Section 4 describes the data and methodology used in the empirical analysis. Section 5 discusses the estimation results. Section 6 presents the demand forecasts until 2040 under different forecast scenarios. And lastly, Section 7 concludes.

2. Review of related literature

There is a wide literature that analyzed residential electricity demand using data from developed countries. The studies can be grouped broadly into two based on the type of data used. One group of studies used household data to analyze household electricity demand using distribution utility prices and reported household income that commonly used a double-log functional form (e.g., Filippini and Pachauri [2004]; Yohanis et al. [2008]). The other group of studies used time series aggregate data, typically expressing residential electricity demand as a function of electricity prices, real incomes (real gross domestic product or real private consumption], and weather conditions. In this group, a common approach is to use an Error Correction Model (e.g., Dilaver and Hunt [2011]; Jamil and Ahmad [2011]; Zachariadis and Pashourtidou [2007]; Halicioglu [2007]; Hondroyiannis [2004]).

Jorgensen and Joutz [2012] analyzed residential electricity demand for the US Mountain Region using an Error Correction Model. The estimates were used to perform two simulations: one is to examine the impact of a ten-percent price increase and the other is to address the effect of an increase in temperature by two degrees Fahrenheit. Explanatory variables used were the real price of electricity, price of natural gas, real personal income per household, and heating and cooling degree-days. Their results show that residential electricity demand is inelastic with respect to price and income in the short run. Meanwhile, weather variables appear as a strong driver of short-run demand.

Donatos and Mergos [1991] estimated per capita residential electricity demand in Greece using a single equation model with ridge regression to overcome the presence of strong multicollinearity. Per capita residential electricity consumption is expressed as a function of private disposable income, the average price of electricity, the weighted average of heating degree days, the average price of LPG, the sales of electrical appliances, the number of consumers, and the average price of diesel. They also found that residential electricity demand is inelastic with respect to price and income, with elasticities of -0.21 and 0.53, respectively. However, they did not find a significant impact of heating degree days since diesel oil is the main energy source for space heating.

Zachariadis and Pashourtidou [2006] examined residential and commercial electricity consumption for Cyprus using an Error Correction Model. Electricity demand is expressed as a function of the lag of income and price, total degree days, and the lag of electricity demand. The error correction term included a dummy variable for the 1974-1975 period to remove the outliers in the series. They found price and income to be insignificant in the short run, and that weather fluctuation has the strongest impact on residential electricity demand.

Hondroyiannis [2004] also used an Error Correction Model to examine how residential electricity demand in Greece is affected by the real price of electricity, real income, population, and the weighted average temperature. Demand is found to be income inelastic and unaffected by price and temperature. They also found that residential electricity demand is not characterized by a structural shift under the period of investigation, thus suggesting that the series is stable and useful for policy purposes.

In the Philippines, there are a few studies that analyzed how electricity demand is affected by various economic and climatic factors. Danao [2001] estimated a short-run model for residential electricity demand in rural areas. After households are partitioned based on their appliance portfolio, demand is estimated for each group as a function of price, annual household expenditure, and household characteristics. Weather variables are not included in the model, like in many studies on electricity demand based on cross-sectional data. His results show that demand is inelastic with respect to both price and income.

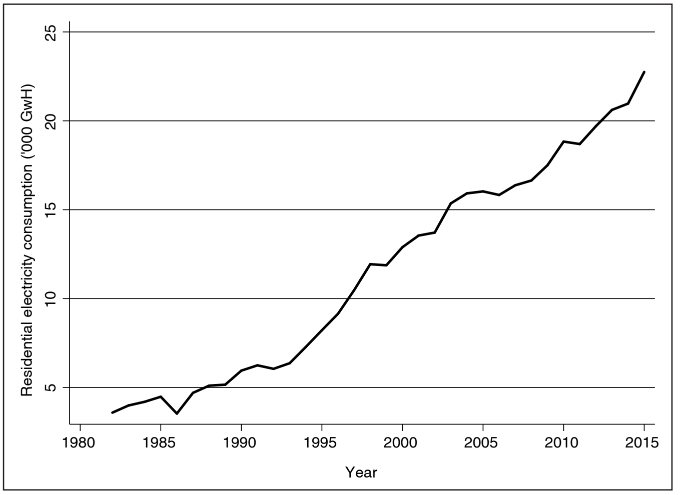
Meanwhile, Danao and Ducanes [2016] used an Error Correction Model to analyze aggregate electricity demand. They used real price, real GDP, and average temperature as explanatory variables. Their results show that aggregate electricity demand has an income elasticity of 0.94, a price elasticity of -0.13, and a temperature elasticity of 1.42. The model performed well in both within-sample and out-of-sample forecasts with a mean absolute percentage error of 1.47 percent and 0.97 percent, respectively. The estimates were then used to perform various simulations for the forecast horizon 2015-2030. By 2030, forecasts of aggregate electricity demand range from 120,000 GWh based on a five percent GDP growth scenario to 150,000 GWh based on a scenario with a seven percent GDP growth, decline in electricity prices by one percent, and increase in temperature by 0.05.

This work adopts the study of Danao and Ducanes [2016] by analyzing the relationship of residential electricity demand with real household income, real price, and temperature using an ECM. It extends the work of Danao [2001] by also analyzing residential electricity demand but using time series data, and by incorporating the effect of weather changes on short-run residential electricity demand.

3. Residential electricity demand over time

Residential demand for electricity in the Philippines has grown significantly over time. Figure 1 plots the upward movement of residential electricity demand across time. It registered an annual growth of 5.8 percent and expanded six folds from 1982 to 2015. It grew faster than commercial or industrial electricity demand, which grew at a rate of 5.7 percent and 3.3 percent, respectively. Residential customers form the largest group of electricity users in 2015, covering 27.6 percent of total electricity demand.

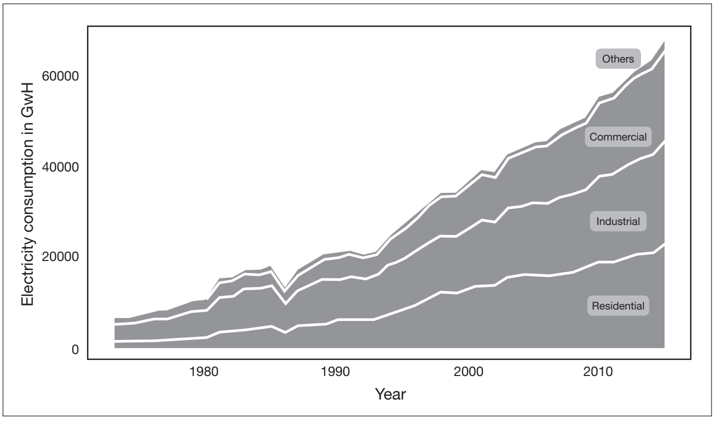
FIGURE 1. Residential electricity demand from 1982 to 2015



Source: Philippine Power Statistics, Department of Energy (DOE)

In the 1980s, demand grew at a slow rate as economic and political crises affected the power industry. A sharp depreciation of the peso made foreign obligations difficult to settle causing the projects of the National Power Corporation (NPC) to be put on hold. Financial difficulties faced by the NPC also dragged down its operational performance. Frequent load shedding occurred between 1983 and 1986 due to power system failures in the Luzon grid. While economic conditions in the 1980s improved, demand for electricity was barely matched by sufficient capacity as NPC's financial difficulties remained.

FIGURE 2. Customer shares to total electricity demand from 1982 to 2015



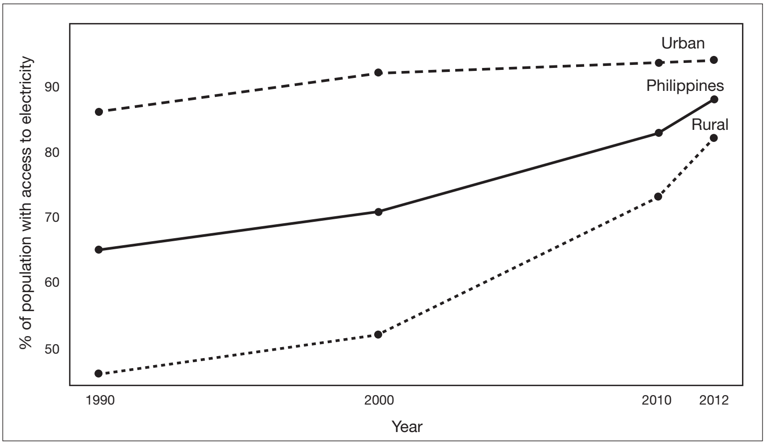
Source: Philippine Power Statistics, Department of Energy (DOE), Philippine Statistical Authority (PSA)

Growth in demand in the late 1980s was disrupted by a power crisis in the early 1990s. From 1990-1993, demand slowed down as the country faced 103 blackout days for an annual duration of 1,273 hours, equivalent to 251 GW of lost energy sales [World Bank 2003]. No new generation capacity was added in the late 1980s given the poor financial position of NPC and the expectations that Bataan Nuclear Power Plant would begin operations in 1984 to meet demand [Cham 2007]. Also, some plants are too old to produce at their installed capacity: available capacity in the Luzon grid ranged from 2,300 to 3,100 MW while installed capacity was 4,321 MW.

From 1994 to 1996, demand grew at a fast rate as the government adopted measures to expedite the creation of new generation capacity. In response to the crisis, the government passed the Power Crisis Act of 1993, which allowed the NPC to enter into "fast-track" contracts with the Independent Power Producers (IPPs) to speed up growth in generation capacity. NPC achieved a relatively stable financial position while MERALCO, the largest power distribution utility, returned to profitability. By 1996, the power sector returned to normal [Cham 2007]. Peak demand in Luzon was at 4,600 MW, while available capacity was in excess of 5,100 MW. Efforts also led to improvement in the electrification rate, which rose to 70 percent by 1996, but rural electrification remained problematic. With excess capacity, load shedding was less frequent and demand became more responsive to changes in economic conditions.

From 1997 to 2015, the NPC again suffered financial difficulties but available capacity remained sufficient to cover demand. The Asian Financial Crisis in 1997 led to a sharp depreciation of the peso that significantly increased the value of NPC's US Dollar-denominated loans, bringing back the NPC to a poor financial situation. On the other hand, the IPPs were not much affected by the Asian Financial Crisis because of the "take-or-pay" clauses in their contracts with NPC [Cham 2007]. In 2001, the government passed the Electric Power Industry Reform Act (EPIRA) which introduced changes in the structure of the power sector and privatized the assets of the NPC. On the demand side, the EPIRA strengthened the responsibility of the Small Power Utilities Group (SPUG) by connecting missionary areas to the grid [Navarro et al. 2016]. From 2000 to 2012, access to electricity in rural areas grew from 52 percent to 82 percent, as shown in Figure 3. This helped expand overall electrification from 71 percent to 88 percent over the same period.

FIGURE 3: Electrification rates over time: total, urban and rural



Source: World Bank, Sustainable Energy for All Database

4. Theoretical framework

Electricity demand is a derived demand. Consumers do not demand electricity in itself, but as an input in the production of electrical services, such as cooling, heating, lighting, and cooking. These services are produced only by supplying electrical power to an electric device. Without electricity, an electric device alone cannot produce an electrical service. And conversely, a consumer without any electric device but only electricity cannot produce an electrical service.

Jorgensen and Joutz [2012] grouped these electrical services into two. One group represents demand for daily use such as lighting, refrigeration, cleaning, and entertainment, while the other represents seasonal weather needs, such as cooling and heating. Price and income generally affect demand across electrical services, while weather conditions mostly affect demand for cooling and heating.

The reduced-form model for residential electricity consumption is formulated as follows:

$$elec=f(price,income,temperature)$$

where *elec* is residential electricity consumption, *price* is residential electricity price, *income* is household income, and *temperature* is annual temperature.

From consumer optimization theory, a demand for a good is influenced by the price of the good and the consumer's income. Assuming electricity demand is a normal good, higher electricity prices reduce demand for electrical service, and also, the demand for electricity. Meanwhile, the higher the income of the household, the higher is the demand for electricity and electrical services. The scale at which these variables can influence demand depends on the elasticity of demand with respect to these variables.

The elasticity of demand with respect to price or income is generally different in the long-run and the short-run. The long-run elasticity of demand is likely to be higher than the short-run elasticity. In the short run, a consumer has a fixed stock of appliances or electric devices that he/she can use to produce an electrical service, and thus, he/she has little room for adjustment in the event of a price or income shock.

A weather variable is also included to capture the effect of the need for electricity. In this study, the temperature is used as a weather variable[1]. The higher the temperature, the higher is the demand for cooling, and thus, the higher the demand for electricity. In the case of countries that experience hot summers and cold winters, the temperature does not have a purely positive relationship with demand. In hot summers, demand for electricity comes from cooling, while in cold winters, demand for electricity comes from heating. In the case of the Philippines that does not experience extremely cold weather conditions, the demand for electricity is expected to be positively related to temperature.

5. Data description and methodology

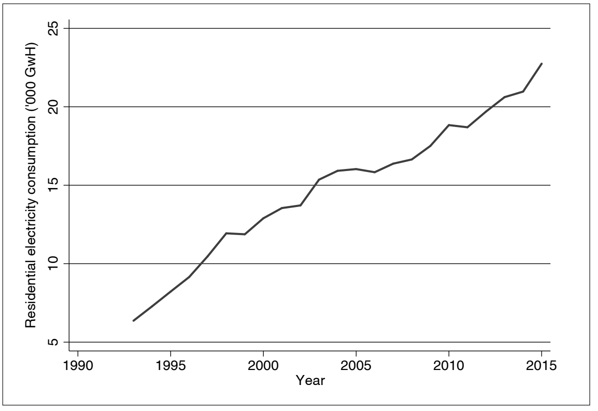
5.1. Data description

The dataset covers 23 annual observations (1993 – 2015) gathered from various sources. The original dataset covers data from 1973 to 2015 but the analysis is limited to more recent observations to avoid the issue of parameter instability, which reduces the forecasting performance of a given model [Pesaran and Timmermann 2002]. For instance, demand from the 1980s and the early 1990s was affected by poor power supply conditions that commonly resulted in load shedding. Since these conditions are no longer the same today, these observations are removed in the analysis to understand the impact of price, income, and temperature more clearly on residential electricity demand.

Residential electricity demand is measured in GWh per year. Data is taken from the Philippine Power Statistics of the Department of Energy (DOE). The Philippine Power Statistics is an annual statistical report containing disaggregated demand for electricity from areas on-grid and off-grid, total power generation mix, and peak demand per major island group. Figure 4.1 shows that residential electricity demand has been growing over time at a rate of 5.96 percent throughout the sample period (1993-2015). From 1993 to 1996, residential electricity demand grew at a faster rate of 12.84 percent as the government expedited measures to increase generation capacity.

[1] Some studies used number of heating degreee days as a weather variable (e.g., Donatos and Mergos [1991]; Hondroyiannis [2004]; Dergiades and Tsouldifis [2008])

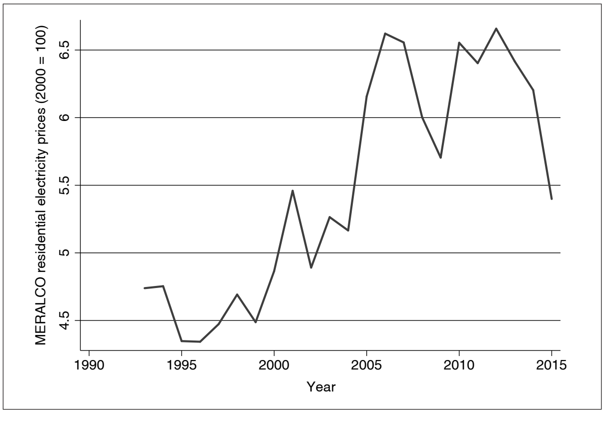
FIGURE 4.1. Residential electricity demand (1993-2015)



Source: DOE

Real residential electricity price[2] is the average annual price per kWh charged by MERALCO to its residential customers. An ideal price data is the average residential electricity price charged by various distribution utilities weighted by their corresponding market shares, but electricity sales of smaller distribution utilities and electric cooperatives are not complete. On the other hand, MERALCO is a leader in the power distribution sector with a market share of around 55 percent to 60 percent of residential electricity demand in the country [Danao and Ducanes 2016]. Real residential electricity prices grew at an average of 0.59 percent per year from 1993 to 2015. Figure 4.2 shows how real residential electricity prices move throughout the sample period.

FIGURE 4.2. Residential electricity price, constant (2000=100), (1993-2015)

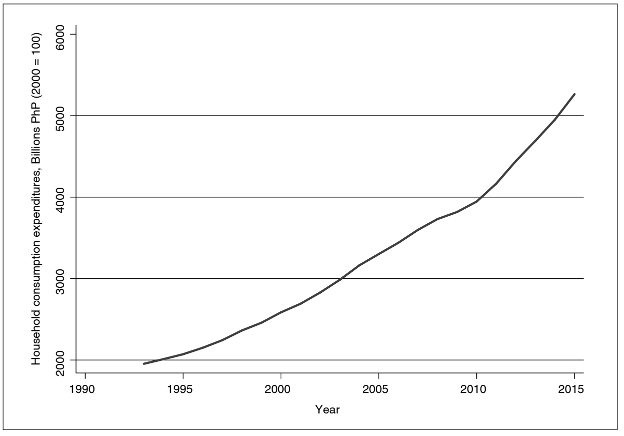


Source: MERALCO

[2] Deflated using GDP deflator (2000=100), following Danao and Ducanes [2016].

Real household final consumption expenditure (2000=100) is gathered from the Philippine Statistical Authority. As shown in Figure 4.3, it has grown steadily over time at an average annual rate of 4.61 percent throughout the sample period. Growth has been faster at around six percent from 2010- 2015.

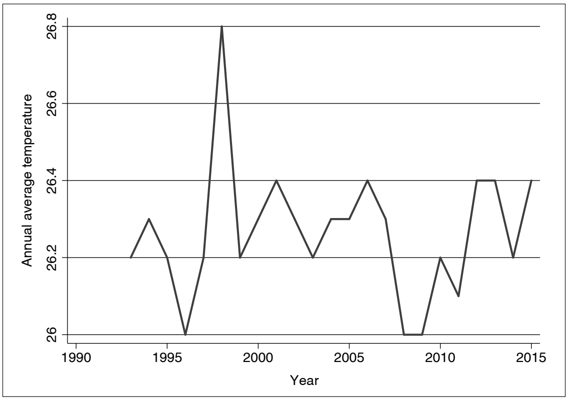
FIGURE 4.3. Household final consumption expenditure, constant (2000=100), (1993-2015)



Source: Philippine Statistical Authority

Annual temperature (in degrees Celsius) is collected from the University of East Anglia Climate Research Unit (CRU). The data is calculated by taking the simple mean of monthly average land temperatures in a given year. Figure 4.4 shows that annual average prices have been fluctuating throughout the sample period and do not display a clear trend. The average temperature is 26.27 degrees Celsius throughout the sample period as shown in Table 1, along with other summary statistics.

FIGURE 4.4. Annual average temperature (1993-2015)



Source: University of East Anglia, Climate Research Unit

TABLE 1. Summary statistics

Variable	Description	Mean	Std. Dev.	Min	Max
hhcons	Residential electricity consumption	14,812	4,535	6,368	22,747
real_price	MERALCO residential electricity prices	5.49	0.83	4.34	6.66
hhfe	Household final consumption expenditure	3,254,644	994,482	1,954,322	5,266,632
temp	Temperature (in Celcius)	26.27	0.17	26	26.80
ln_cons	log of residential electricity consumption	9.55	0.35	8.76	10.03
ln_price	log of MERALCO residential electricity prices	1.69	0.15	1.47	1.90
ln_temp	log of temperature (in Celcius)	3.27	0.01	3.26	3.29
ln_hhfe	log of household final consumption expenditure	14.95	0.31	14.49	15.48

Source: Author's calculations

5.2. Methodology

Among electricity demand studies that used time series models, cointegration models were commonly used. When the variables are cointegrated, the OLS estimator is super-consistent and allows the estimate to converge to its true value at a faster rate [Stock 1997]. Cointegration models establish the existence of a long-run equilibrium relationship tying the individual variables and therefore, "imposing this information can produce substantial improvements in forecasts over long horizons" [Stock 1997]. However, cointegration models may be used only if the variables are found to be cointegrated. If the variables are not cointegrated, a common resort is to use an ARDL model that expresses the dependent variable as a function of the explanatory variables, their respective lags, and, the lags of the dependent variable.

A common approach to test for cointegration is the Engle-Granger [1987] two-step procedure. It tests for cointegration by determining whether the linear combination of non-stationary variables is stationary. This approach entails two simple steps. The first step is to predict the residual using a standard OLS on a chosen long-run equation. The second step is to determine whether the predicted residual is stationary using unit root tests[3].

If the variables are found to be cointegrated, the ECM can be used. This model involves estimating the lag of the residual from the long-run equation. This lagged residual is also known as the error correction term. The coefficient of the error correction term must be negative to indicate that a positive short-run deviation would be corrected by a movement back towards the long-run equilibrium. The larger the coefficient, in absolute terms, the faster the dependent variable moves back to the long-run equilibrium after a short-run deviation.

[3] Common unit root tests are Dickey-Fuller test and the Philips-Perron test

Algebraically, the Error Correction Model can be derived from an ARDL equation. For example, consider the following simple ARDL model:

$$Y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 y_{t-1} + u_t \qquad (1)$$

wherein the equation y_t is the log of residential electricity demand, expressed as a linear function of the log of household income, x_t its lags, x_{t-1}, and the lag of the dependent variable, y_{t-1}. For stability, the condition $|\beta_3| < 1$ is imposed.

The variables would reach a long-run equilibrium characterized as follows:

$$y_t = y_{t-1} \qquad (2)$$

$$x_t \quad x_t \qquad (3)$$

Plugging in these long-run equilibrium values (Equations (2) and (3) into the ARDL equation (Equation 1), the long-run demand equation is derived as follows:

$$y_t = \beta_0/(1-\beta_3) + (\beta_1 + \beta_2)x_t/(1-\beta_3) + u_t/(1-\beta_3) \qquad (4)$$

In equation 4, the long-run elasticity of demand with respect to x_t is $(\beta_1 + \beta_2)/(1-\beta_3)$.

Letting $e_t = u_t/(1-\beta_3)$, Equation (4) can be rewritten as:

$$y_t = \beta_0/(1-\beta_3) + (\beta_1 + \beta_2)x_t/(1-\beta_3) + e_t \qquad (5)$$

Subtracting y_{t-1} from both sides of Equation (5):

$$\Delta y_t = \beta_0/(1-\beta_3) - y_{t-1} + (\beta_1 + \beta_2)x_t/(1-\beta_3) + e_t \qquad (6)$$

Adding and subtracting in the right-hand side would derive the ECM:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t - (1-\beta_3)\left[y_{t-1} - (\beta_1 + \beta_2)x_{t-1}/(1-\beta_3)\right] + e_t \qquad (7)$$

In equation (7), the short-run elasticity of demand with respect to x_t is measured by the coefficient, β_1. The term $(1-\beta_3)\left[y_{t-1} - (\beta_1 + \beta_2)x_{t-1}/(1-\beta_3)\right]$ is the error correction term that adjusts short-run demand towards the long-run equilibrium relationship following a short-run deviation. The coefficient $(1-\beta_3)$ measures the speed of adjustment.

6. Estimation results

The set of analyses below involves four steps. First, the order of integration of each variable is determined using different unit root tests, including the Augmented Dickey-Fuller Test, along with two other efficiency tests developed by Elliott, Rothenberg, and Stock [1996]. Second, a long-run equation is specified and an Engle-Granger test is used to determine the presence of a cointegrating relationship. Third, a test of weak exogeneity is conducted to determine whether a feedback mechanism exists that would necessitate the use of a Vector Autoregression (VAR) model rather than a single equation model [Enders 2015]. And lastly, an ECM equation is estimated, and standard diagnostic and parameter stability tests are conducted.

6.1. Orders of integration

A regression involving variables with different orders of integration may yield spurious results unless these variables are cointegrated. Hence, it is important to determine the order of integration of each variable using unit-root tests, of which, the most common is the Augmented Dickey-Fuller (ADF) Test. The ADF tests the null hypothesis that the series has a unit root, or integrated of order 1, or more. If a series has a unit root in levels but not in the first difference, then the variable is said to exhibit an I(1) process. If a series in levels does not have a unit root, the variable is said to exhibit an I(0) process. Alternatively, the order of integration can be determined visually using a correlogram. A correlogram shows how the variable is correlated with its own lags. A correlogram that shows a declining pattern strongly suggests non-stationarity or the presence of unit roots.

An alternative to the two-unit root tests above is taken from a family of efficient tests developed by Elliott, Rothenberg, and Stock (ERS) [1996] whose modifications improved test performance relative to an ordinary Dickey-Fuller test for series characterized with small sample size. Among the family of tests is the feasible point optimal test whose asymptotic power function is tangent to the power envelope and never far below it. A specification of this test that detrends series with intercept and trend is used as a comparison for the ADF Test. Also used is another test within the same family called the Dickey-Fuller Generalized Least Squares (DF-GLS), which modifies the ordinary Dickey-Fuller Test by transforming the series via a generalized least squares regression [ERS 1996].

Results of the ADF tests (see Table 2.1) show that the variables have different orders of integration: the log of residential electricity demand (ln_cons), the log of real price (ln_price), and the log of household final consumption expenditure (ln_hhfe) are I(1), while the log of temperature is I(0). Likewise, a visual analysis of the correlograms for these same variables (see Figures 5.1-5.8) agrees with the results of the ADF tests. These tests are then compared with the results of the feasible point optimal tests and DF-GLS tests. Results of the ADF tests are not entirely different from those of the ADF tests with the exception of the log of residential electricity consumption variable wherein the presence of a unit root cannot be rejected. However, as the DF-GLS agrees with the ADF tests in indicating a unit root process for the log of residential electricity consumption, the first differences are used in the short-run estimations below.

TABLE 2.1. Results of the ADF and Elliott, Rothenberg, and Stock (ERS) tests

		ADF Test statistics		Feasible Optimal Test [ERS 1996] Test Statistics		DF-GLS [ERS 1996] Test Statistics	
Variable	Description	in log-levels	in 1st difference	in log-levels	in 1st difference	in log-levels	in 1st difference
ln_cons	Residential electricity consumption	-2.183	-3.468***	82.257	10.713	-1.417	-4.16***
ln_price	Residential electricity price	-1.393	-4.413***	9.755	6.555*	-1.955	-4.609***
ln_hhfe	Household consumption expenditure	2.209	-4.578***	4.70**	6.432*	-3.253**	-2.5
ln_temp	Temperature	-4.129***	-3.677***	4.07***	2.391***	-2.259	-3.15**

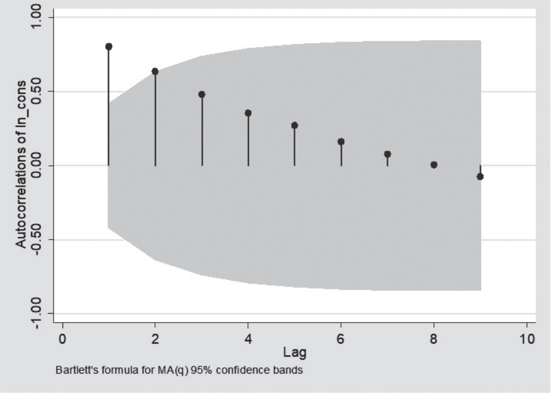
Source: Author's calculations
****p*<0.01, ***p*<0.05, **p*<0.10

TABLE 2.2. Lag specifications for the ADF and ERS tests

		ADF Test statistics		Feasible Optimal Test [ERS 1996] Test Statistics		DF-GLS [ERS 1996] Test Statistics	
Variable	Description	in log-levels	in 1st difference	in log-levels	in 1st difference	in log-levels	in 1st difference
ln_cons	Residential electricity consumption	2	0	4	4	4	0
ln_price	Residential electricity price	0	0	2	2	2	0
ln_hhfe	Household consumption expenditure	0	7	4	4	4	0
ln_temp	Temperature	0	2	4	4	4	4

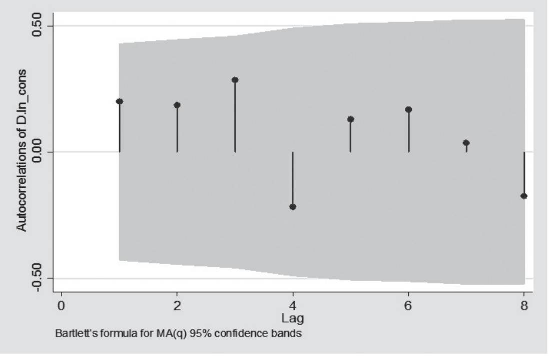
Source: Author's calculations

FIGURE 5.1. Correlogram of ln_cons



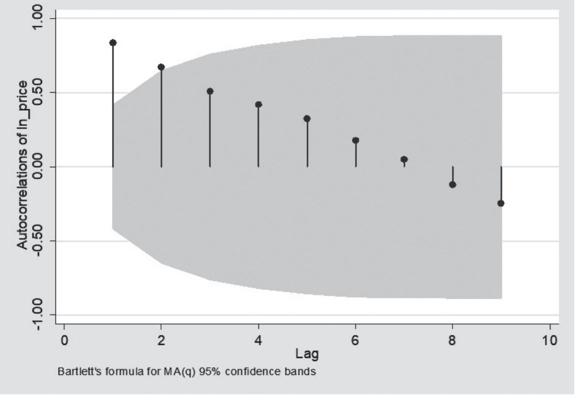
Source: Author's calculations

FIGURE 5.2. Correlogram of D.ln_cons



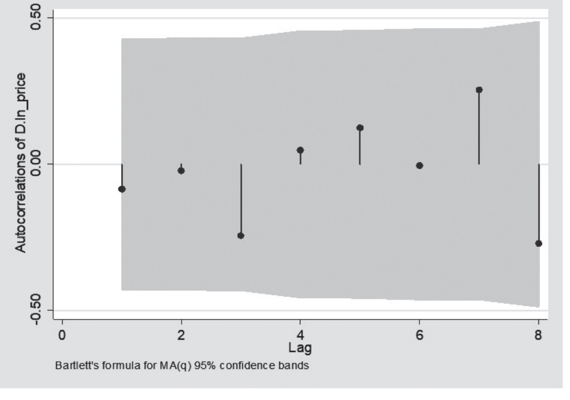
Source: Author's calculations

FIGURE 5.3. Correlogram of ln_price



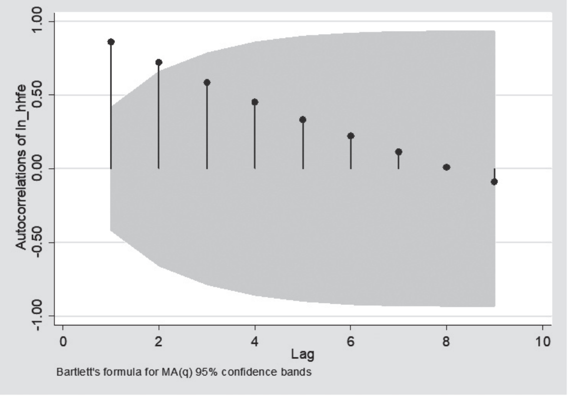
Source: Author's calculations

FIGURE 5.4. Correlogram of D.ln_price



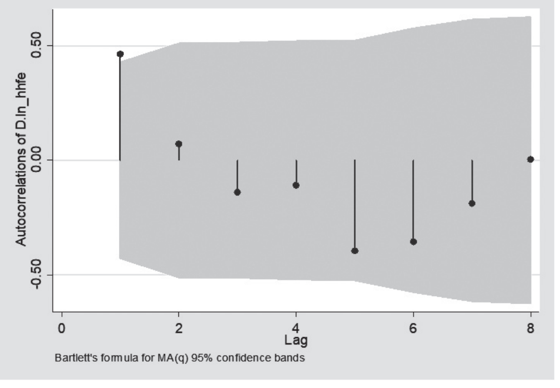
Source: Author's calculations

FIGURE 5.5. Correlogram of ln_hhfe



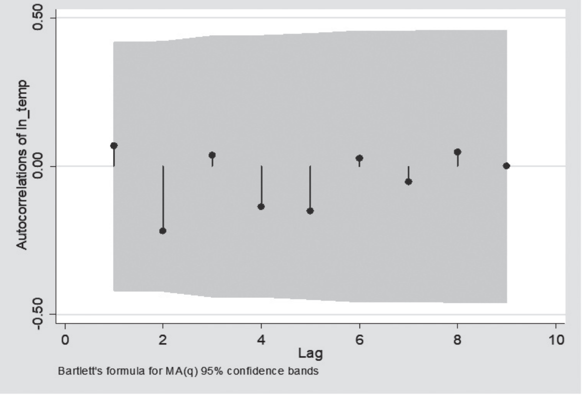
Source: Author's calculations

FIGURE 5.6. Correlogram of D.ln_hhfe



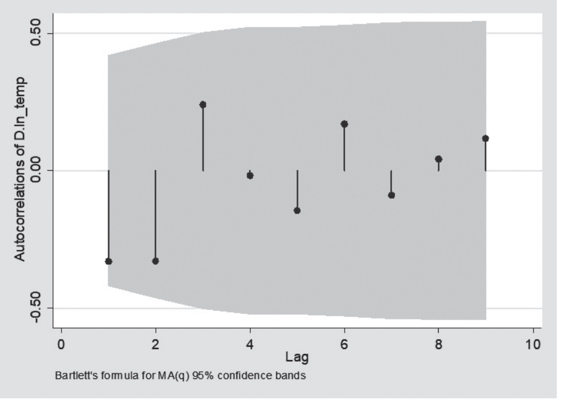
Source: Author's calculations

FIGURE 5.7. Correlogram of ln_temp



Source: Author's calculations

FIGURE 5.8. Correlogram of D.ln_temp



Source: Author's calculations

6.2. Granger Causality Test

This part of the analysis aims to understand whether bidirectional feedback exists between household expenditures and residential electricity consumption. Some studies have found that a bidirectional causality exists between economic growth and aggregate electricity consumption (e.g., Odhiambo [2009]; Bayar & Ozel [2014]). To determine whether such a feedback mechanism exists, a Granger causality test is used. If an F-test shows that a dependent variable can be explained by an autoregressive lagged specification of both the dependent and independent variables, then the independent variable is said to Granger-cause the dependent variable [Granger 1969]. A feedback mechanism exists if household expenditures Granger-cause residential electricity consumption, and vice versa.

The resulting F-tests of the model with lags of 4 are shown in Table 3 below. The resulting F-test is significant at the one percent significance level for the autoregressive model with the residential electricity consumption as the dependent variable; thus, suggesting that household expenditures Granger-causes residential electricity consumption. However, the reverse is not true as the lags of residential electricity consumption do not explain household expenditures. One important implication of this result is that estimating the long-run equation for the log of residential electricity consumption is unlikely to suffer from endogeneity bias.

TABLE 3. Results of the Granger causality test

Equation	Explanatory variable	*F*-statistic
ln_cons	ln_hhfe	23.05***
ln_hhfe	ln_cons	1.66

***p<0.01

Source: Author's calculations

6.3. Test for cointegration

The Engle-Granger test is used to determine whether the variables *ln_cons* and *ln_hhfe* are cointegrated. The graphs of the logs of residential electricity demand and household final consumption expenditure exhibit strong co-movement throughout the sample period (1993-2015) with a correlation of 95 percent, suggesting that these variables may be cointegrated. Equation 8 shows a model that includes a dummy variable, *dum1996* to account for the change in the movement of residential electricity demand as the power supply situation returned to normal in 1996 following the government responses to the power crisis in 1993 [Cham 2007]. Equation (8) below is estimated using OLS, then the residual is tested for stationarity based on Engle-Granger test statistics. OLS results for Equation (8) are found in Table 4 below.

$$ln\_cons_t = \alpha_0 + \alpha_1 ln\_hhfe_t + \alpha_2 dum1996 + u_t \qquad (8)$$

where: ln_cons_t is the logarithm of residential electricity consumption,
ln_hhfe_t is the logarithm of household final consumption expenditure in 2000 prices,
$dum1996$ takes the value 1 if the year is 1996 or above, and 0, otherwise.

TABLE 4. OLS results of the long-run model (Equation 8)

VARIABLES	(1) ln_cons
ln_hhfe	0.878***
	(0.0502)
dum1996	0.320***
	(0.0445)
Constant	-3.850***
	(0.729)
Observations	23
R-squared	0.974

Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Source: Author's calculations

The results of the Engle-Granger test (see Table 5) support the hypothesis that residential electricity consumption and household final consumption expenditure have a long-run relationship. The Engle-Granger test statistic is -4.61, rejecting the null hypothesis of no cointegration at the five percent level of significance.

TABLE 5. Result of the Engle-Granger Test

	Critical Values		
Test statistic	**1 percent**	**5 percent**	**10 percent**
-4.612	-5.014	-4.15	-3.742

Source: Author's calculations

Since the variables ln_hhfe_t and ln_cons_t are cointegrated, an ECM can be used to analyze relationships of price and income with residential electricity demand. Instead of a two-step ECM, which involves predicting the residual and using the predicted lag of the residual (i.e., u_{t-1}) as part of the short-run ARDL model, the one-step ECM is used such as the one shown in Equation (9) below. The latter estimates include the lag of the cointegrated variables: ln_cons_{t-1} and ln_hhfe_{t-1} in lieu of u_{t-1}. While unit root tests suggest that *ln_temp* is I(0), it is expressed in the first differences in the ECM for a more direct interpretation of its coefficient.

$$\Delta ln\_cons_t = \beta_1 \Delta ln\_hhfe_t + \beta_2 \Delta ln\_price_{t-1} + \beta_3 \Delta ln\_temp_t + \beta_4 ln\_hhfe_{t-1} + \beta_5 ln\_cons_{t-1} + e_t \quad (9)$$

where: Δln_cons_t is the first difference of the logarithm of residential electricity consumption,

$\beta_1 \Delta ln\_hhfe_t$ is the first difference of the logarithm of household final consumption expenditure in 2000 prices,

Δln_price_{t-1} is the lag of the first difference of the logarithm of real residential electricity price,

Δln_temp_t is the first difference of the logarithm of temperature,

ln_hhfe_{t-1} is the lag of the logarithm of household final consumption expenditure in 2000 prices,

ln_cons_{t-1} is the lag of the logarithm of residential electricity consumption

6.4. Test of weak exogeneity

In a single-equation ECM, it is important that the cointegrating vector is unique[4] and the explanatory right-hand side variables are weakly exogenous [Harris 1995]. A variable is said to be weakly exogenous if its marginal distribution contains no useful information for conducting inference on a parameter set (Engle et al. [1983]; Enders (2015)]. If the variables are weakly exogenous, a single-equation ECM (as shown in Equation (9)) can be used to analyze relationships. Each of the variables used in the right-hand side of the short-run model is regressed on the lagged residual, and then, a *t*-test is performed on the variable, u_{t-1}. Results (see Table 6) show that none of the variables is significant at the five percent level, suggesting that the variables are weakly exogenous. This satisfies the requirement of Harris [1995] in the use of single-equation ECM.

Table 6. Results of the test of weak exogeneity

Test of weak exogeneity	D.ln_hhfe	D.L.ln_price	D.ln_temp
L.uhat	0.03	0.35	0.04
p-value	0.14	0.07	0.32

Source: Author's calculations

[4] By definition, a single explanatory variable in the long-run model means that the cointegrating vector is already unique.

6.5. Results of the ECM and the ARDL

Estimates of the ECM are consistent with economic theory (see Table 7, model 1) and passed standard diagnostic tests (see Table 8, model 1). The first column of Table 6 shows the estimates using the ECM. First, price and household final consumption expenditure have a negative and a positive effect on household electricity demand, respectively. Estimated short-run price elasticity is -0.26, while short-run income elasticity is 0.75, although not significant at the ten percent level. Second, the estimated long-run elasticity[5] is 1.75, higher than the short-run elasticity estimate. This suggests that households do not immediately adjust to income shocks until they are able to adjust appliance stock in the long-run. Third, the temperature has an elasticity of 2.2 indicates that demand is highly elastic with respect to changes in temperature. High-temperature levels trigger households to use cooling appliances, such as an air conditioner, which typically consumes a large amount of electricity. The model also passed the parameter stability test, as the graph of the CUSUM-squared test (see Figure 6.1) is within five percent bandwidth of significance.

TABLE 7. Results of the ECM and the ARDL

	(ECM)	**(ARDL)**
VARIABLES	**D.ln_cons**	**D.ln_cons**
D.ln_hhfe	0.754	-0.582
	(0.438)	(0.764)
LD.ln_price	-0.264***	-0.329***
	(0.0570)	(0.102)
D.ln_temp	2.206***	2.587***
	(0.456)	(0.878)
L.ln_cons	-0.206***	
	(0.0517)	
L.ln_hhfe	0.118**	
	(0.0540)	
Constant	0.237	0.0847**
	(0.361)	(0.0356)
Observations	21	21
R-squared	0.893	0.545

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's calculations

[5] Long-run income elasticity is calculated by dividing the coefficient of L.ln_cons by the coefficient of L.ln_hhfe. This calculation is based on Equation (7) in the Theoretical Framework.

TABLE 8. Standard diagnostic test results (*p*-values)

Diagnostic tests	Model 1 (ECM)	Model 2 (ARDL)
RAMSEY Reset Test	0.961	0.560
Test for Heteroskedasticity	0.441	0.099
Breusch-Godfrey Test for serial correlation	0.241	0.025
Jarque-Bera normality test	0.260	0.260

Source: Author's calculations

For comparison, the following ARDL model (Equation (10)) is also estimated:

$$\Delta ln\_cons_t = \beta_1 \Delta ln\_hhfe_t + \beta_2 \Delta ln\_price_{t-1} + \beta_3 \Delta ln\_temp_t + e_t \qquad (10)$$

where: Δln_cons_t is the first difference of the logarithm of residential electricity consumption

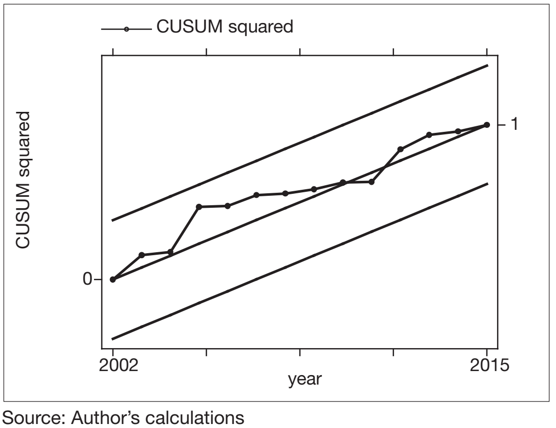
$\beta_1 \Delta ln\_hhfe_t$ is the first difference of the logarithm of household final consumption expenditure in 2000 prices

Δln_price_{t-1} is the lag of the first difference of the logarithm of real residential electricity price

Δln_temp_t is the first difference of the logarithm of temperature

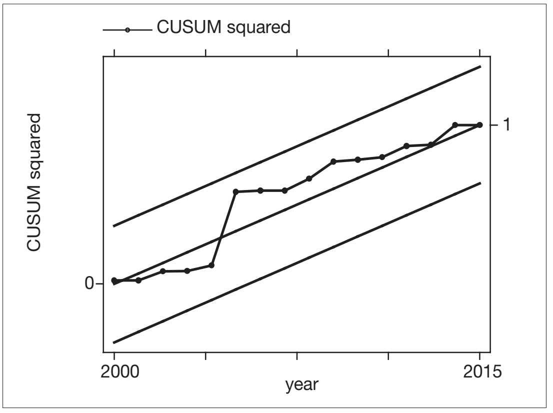
Results for the ARDL are found in the second column of Table 7. The only difference of the ARDL model from the ECM is the exclusion of the error correction term. The price elasticity is -0.33 and the temperature elasticity is 2.59. On the other hand, income elasticity is not significantly different from zero and has a negative sign, a result also found by Jorgensen and Joutz [2012]. The model generally passed standard diagnostic tests (see Table 8, model 2), except for the Breusch-Godfrey test indicating the presence of serial correlation. Also, the graph of the CUSUM-squared test (see Figure 6.2) is within the five percent bandwidth, which means the parameters are stable.

FIGURE 6.1. Parameter stability test for ECM (CUSUM Test)



Source: Author's calculations

FIGURE 6.2. Parameter stability test for ARDL (CUSUM Test)



Source: Author's calculations

6.6. Forecasting performance

The forecast accuracy of the two models is compared using the Mean Absolute Percentage Error (MAPE) of both in-sample and out-of-sample forecasts, with a hold-out period from 2012 to 2015. The MAPE is calculated by taking the absolute value of the difference between the actual and forecast values as a fraction of the actual value. The forecasting performance of the ECM is superior to that of the simple ARDL. For the ECM, the out-of-sample MAPE is 6.32 percent while the within-sample MAPE is 1.13 percent. In contrast, for the ARDL model, the out-of-sample and within-sample MAPEs are higher at 2.38 percent and 9.19 percent, respectively. The graphs comparing actual and forecasted values for residential electricity consumption for the estimated period are shown in Figure 7.1 for ECM and Figure 7.3 for ARDL. The graphs of the out-of-sample forecasts for ECM are in Figure 7.2 and for ARDL in Figure 7.4.

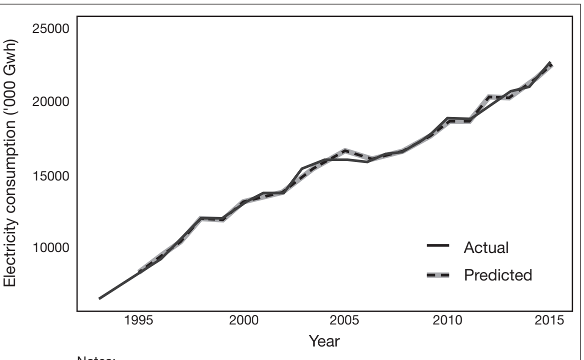
TABLE 9. Mean absolute percentage error of estimates from ECM and ARDL

ECM: Mean Absolute Percentage Error (MAPE)	
in-sample	1.13 percent
out-of-sample	6.32 percent

ARDL: Mean Absolute Percentage Error (MAPE)	
in-sample	2.38 percent
out-of-sample	9.19 percent

Source: Author's calculations

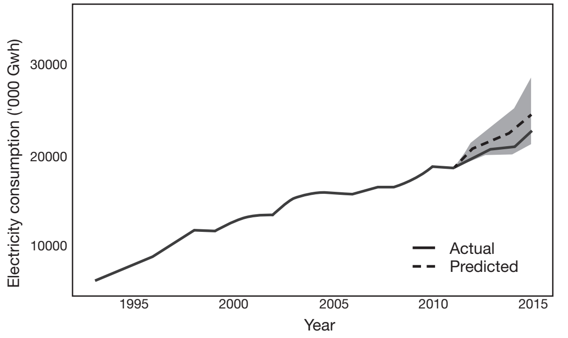
FIGURE 7.1. Comparison of actual and within-sample forecasts using ECM



Notes:
1. Predicted values shown are based on the ECM.
2. Confidence bands for predicted values are displayed.

Source: Author's calculations

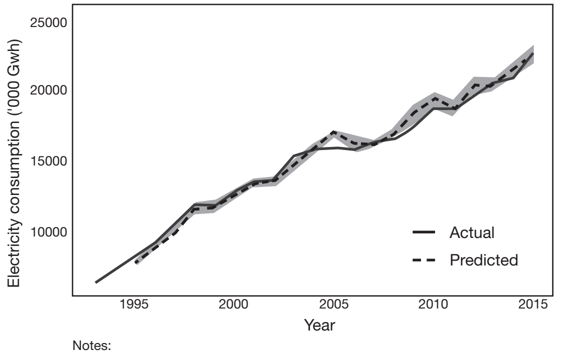
FIGURE 7.2. Comparison of actual and out-of-sample forecasts using ECM



Notes:
1. Predicted values shown are based on the ECM.
2. Confidence bands for predicted values are displayed.

Source: Author's calculation

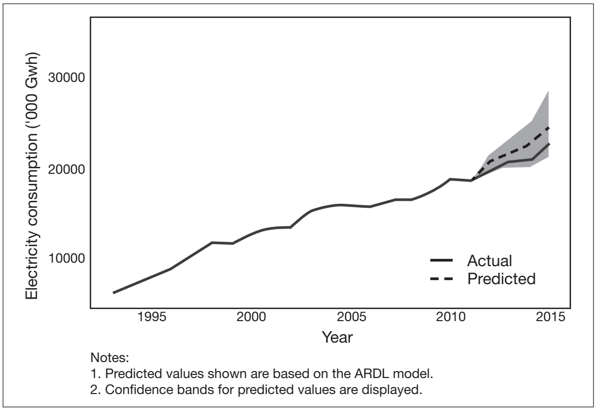
FIGURE 7.3. Comparison of actual and within-sample forecasts using the ARDL



Notes:
1. Predicted values shown are based on the ARDL model.
2. Confidence bands for predicted values are displayed.

Source: Author's calculations

FIGURE 7.4. Comparison of actual and out-of-sample forecasts using the ARDL



Source: Author's calculations

7. Scenario analysis

The Error Correction Model is used to forecast residential electricity demand from 2016 to 2040. The ECM has a better forecasting performance than the alternative short-run ARDL model, it passed standard diagnostic and parameter stability tests, and has elasticity estimates consistent with economic theory.

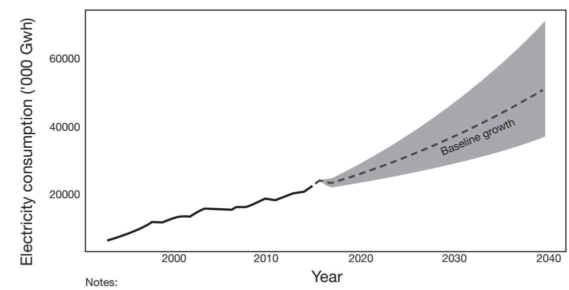
There are six scenarios used to forecast long-term residential electricity demand, as adopted from the scenarios used by Danao and Ducanes [2016]. All the scenarios assume a GDP growth rate of six percent per year. The first three scenarios assume different growth rates for household final consumption expenditures HHFE while assuming that the other explanatory variables follow historical trends, i.e., the predicted values using the time variable as a regressor. The three scenarios are the following: (1) the baseline scenario wherein HHFE grows at an annual rate of six percent (also the average growth from 2011-2015); (2) the strong growth scenario wherein HHFE grows at an annual rate of seven percent; (3) the weak growth scenario or non-consumption-driven growth wherein real GDP growth of six percent is driven by growth of total real GDP less real household final consumption expenditure (i.e., I+G+NX) growing at 8 percent, with an implied growth rate of 4.7 percent. The fourth scenario assumes that temperature follows historical trend, real HHFE grows at six percent, while household electricity price falls by one percent per year. The fifth scenario assumes temperature will increase by 0.05 per year[6], while price follows the historical trend and real HHFE grows at an average of six percent. And lastly, the sixth scenario is the combined growth scenario which assumes that the price will fall by one percent, the temperature will increase by 0.05, and real HHFE will grow by seven percent per year.

[6] This figure is based on the study of Cinco, et al. [2013] that projects temperature in the Philippines to increase by 0.9 and 1.1 from 2000 to 2020. The annual average increase in temperature using the midpoint projection of 1.0 is 0.05

7.1. Impact of growth in Household Final Consumption Expenditure (HHFE)

Higher growth of HHFE results in higher growth of residential electricity demand in the future. The baseline scenario assumes HHFE growth of six percent per year, the strong growth scenario assumes HHFE growth of seven percent, while the weak growth scenario assumes that the six percent assumed growth in real GDP is driven by eight percent growth in components other than consumption, i.e., (I+G+NX), while HHFE grows at only 4.7 percent. Under the baseline scenario, residential electricity demand will grow at 3.20 percent per year, while the weak consumption and strong consumption growth scenarios yield an annual average residential electricity demand growth of 2.43 percent and 3.78 percent, respectively. By 2040, residential electricity demand under the weak growth scenario is 17.04 percent lower than the baseline forecast while that under the strong growth scenario is 15.28 percent higher than the baseline forecast. Figure 8.1 compares the forecasts for each growth scenario.

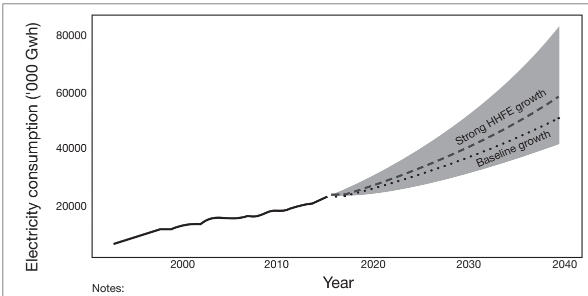
FIGURE 8.1. Simulations based on the baseline growth scenario (in GWh)



Notes:
1. Under the baseline househould expenditures (HHFE) growth scenario, HHFE grows at 6% while price and temperature follows historical trend.
2. Confidence bands for baseline HHFE growth scenario are displayed.

Source: Author's calculations

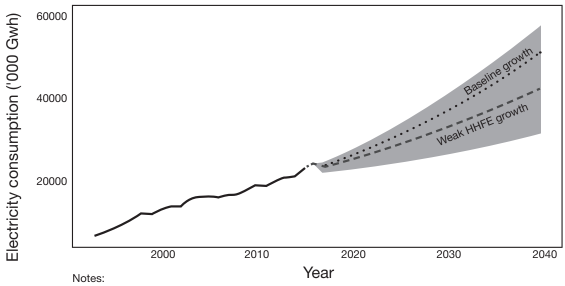
FIGURE 8.2. Simulations based on the strong growth scenario (in GWh)



Notes:
1. Under the strong househould expenditures (HHFE) growth scenario, HHFE grows at 7% while price and temperature follows historical trend.
2. Confidence bands for strong HHFE growth scenario are displayed.

Source: Author's calculations

FIGURE 8.3. Simulations based on the weak growth scenario (in GWh)



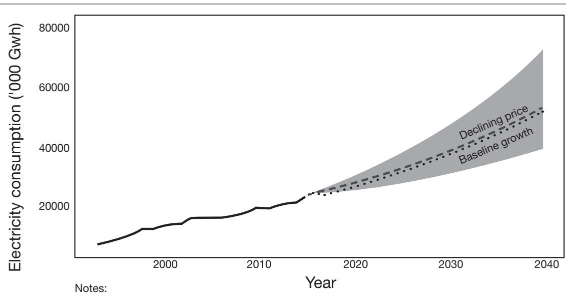
Notes:
1. Under the weak househould expenditures (HHFE) growth scenario, HHFE grows at 4.7% while price and temperature follows historical trend.
2. Confidence bands for weak HHFE growth scenario are displayed.

Source: Author's calculations

7.2. Impact of a price decline

Declining residential electricity prices result in higher growth of residential electricity demand in the future. This scenario assumes a decline in residential electricity prices by one percent per year, an increase in temperature following the historical trend, and an HHFE growth of six percent per year. From 2016 to 2040, residential electricity demand will grow at 3.31 percent per annum, and by 2040, residential electricity demand will reach 52,689 GWh, higher than the baseline scenario by only 2.85 percent. The minimal increase relative to the baseline scenario is expected considering the low-price elasticity of residential electricity demand, in absolute terms. Figure 8.4 compares the forecasts between baseline HHFE growth and the price decline scenario.

FIGURE 8.4. Simulations based on the declining price scenario (in GWh)



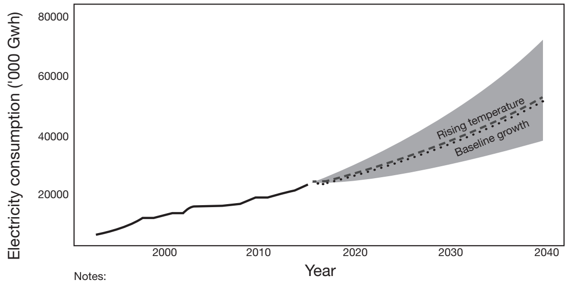
Notes:
1. Under the declining price scenario, residential electricity price declines annually by 1% while HHFE grows at 6% and temperature follows historical trend.
2. Confidence bands for the declining price scenario are displayed.

Source: Author's calculations

7.3. Impact of increasing temperature

Increasing temperatures result in higher growth of residential electricity demand in the future. This scenario assumes a uniform increase in temperature by 0.05 per year based on projections by Cinco, et al [2013], an increase in electricity prices following the historical trend, and a growth of HHFE by six percent per year. From 2016-2040, residential electricity demand will grow at 3.22 percent per annum, and by 2040, residential electricity demand will reach 52,243 GWh, higher than the baseline scenario by 1.98 percent. Figure 8.5 compares the forecasts between baseline HHFE growth and the increasing temperature scenario.

FIGURE 8.5. Simulations based on rising temperature scenario (in GWh)



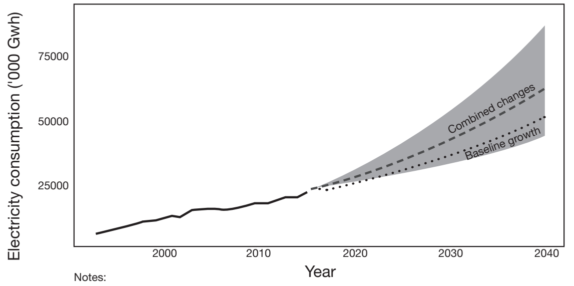
Notes:
1. Under the rising temperature scenario, average temperature rises incrementally by 0.05 °C while HHFE grows at 6% and price follows historical trend.
2. Confidence bands for the rising temperature scenario are displayed.

Source: Author's calculations

7.4. Impact of combined changes in the explanatory variables

Among the scenarios adopted in this paper, this scenario yields the highest forecast of residential electricity demand. This scenario assumes growth in HHFE by seven percent, a decline in residential electricity prices by one percent, and a uniform increase in temperature by 0.05 per year. From 2016-2040, residential electricity demand will grow at 3.91 percent per annum, and by 2040, residential electricity demand will reach 61,942 GWh, higher than the baseline scenario by 20.91 percent. Figure 8.6 compares the forecasts between baseline HHFE growth and the combined changes scenario.

FIGURE 8.6. Simulations based on combined changes scenario (in GWh)



Notes:
1. Under the combined changes scenario, average temperature rises incrementally by 0.05 °C, HHFE grows at 7% and price follows declines by 1%.
2. Confidence bands for the combined changes scenario are displayed.

Source: Author's calculations

TABLE 10. Summary of forecasts under various scenarios

Scenario	Assumptions on variables	2030 (in GWh)	2040 (in GWh)
Baseline growth	HHFE annual growth: 6 percent Price: historical trend Temp: historical trend	36,648	51,230
Strong growth	HHFE annual growth: 7 percent Price: historical trend Temp: historical trend	40,036	59,060
Weak growth	GDP growth of 6 percent and non-consumption growth (I+G+NX) of 8 percent Price: historical trend Temp: historical trend	33,251	42,500
Price decline	GDP annual growth: 6 percent Price: decline by 1 percent per year Temp: historical trend	37,811	52,689
Temperature increase	GDP annual growth: 6 percent Price: historical trend Temp: increase by 0.05 per year	37,380	52,243
Combined changes	GDP annual growth: 7 percent Price: decline by 1 percent per year Temp: increase by 0.05 per year	42,132	61,942

Source: Author's calculations

8. Conclusion

This paper analyzed how residential electricity consumption responds to changes in income, price, and temperature using an ECM. The forecast performance of the ECM is superior to that of the ARDL based on historical simulations. Estimates were used to forecast residential electricity demand until 2040 using various scenarios adopted from Danao and Ducanes [2016].

The estimates satisfied various conditions that are important in using an ECM. The logs of residential electricity demand, price, and household final consumption expenditure are integrated of order 1, while the log of temperature is integrated of order zero. The variables are transformed into first differences so that the ECM involved variables with the same order of integration. The Engle-Granger test showed that the log of residential electricity demand is cointegrated with the log of household final consumption expenditure. Also, evidence of weak exogeneity is found in the explanatory variables.

Estimates show that demand responds negatively to prices, positively to income and temperature. Long-run elasticity for real household final consumption expenditure is larger than in the short run since households can adjust the stock of appliances in the long-run and thus, be more responsive to changes in income. Meanwhile, the short-run estimates for price and income fall within the bounds reported in the meta-analysis of Espey and Espey [2004]. Each of the models passed standard diagnostic and parameter stability tests. The forecasting performance of the ECM for long-run simulations is better than the ARDL. Despite the limited sample size used in estimating the elasticities, the out-of-sample predictions were highly accurate.

Scenario analysis provides a range of possible values of long-term residential electricity demand. The simulations are compared to that of the baseline six percent growth in household final consumption expenditure. By 2040, the weak growth scenario provides the most conservative forecast, lower by 17 percent than the baseline scenario, while the combined changes scenario provides the most aggressive forecast, higher by around 21 percent than the baseline scenario. The strong household consumption growth scenario also provides a high forecast considering the fairly high long-run elasticity of demand with respect to income.

Future research can extend this work by using alternative techniques to estimate demand elasticities. For instance, in testing for cointegration, it would be worth exploring how the results would be different using an ARDL-bounds test. Also, using a longer time series data that examines structural breaks would likely increase the degrees of freedom and improve the quality of estimates. Along with the forecasts for residential consumption, forecasting industrial and commercial consumption are also important for policymakers. These customer groups have dynamics separate from what is analyzed in this paper. Future works that investigate consumption behavior from these customer groups are recommended.

These results are useful to guide policymakers in determining the size of future expansion in generation capacity to ensure that future electricity demand is adequately met. The Philippines has experienced situations in the past wherein generation capacity was not able to meet demand leading to frequent load shedding. Policymakers need to ensure that such situations are prevented from occurring in the long-term. Thus, it is critical for energy policy planners to have an accurate estimate of electricity demand growth over time.

References

Alabbas, N. & J. Nyangon [2016] "Weather-based long-term electricity demand forecasting model for Saudi Arabia: a hybrid approach using end-use and econometric methods for comprehensive demand analysis, in implications of North American energy self-sufficiency", 34th USAEE/IAEE North American Conference, Oct 23-26, 2016. International Association for Energy Economics.

Bayar, Y. & H. Ozel [2014] "Electricity consumption and economic growth in emerging economies", *Journal of Knowledge Management, Economics and Information Technology* 4(2).

Cham, M. [2007] "Philippine power sector: issues and solutions", *Philippine Review of Economics* 46(1): 33-63.

Cinco, T., et al. [2013] "Climate trends and projections in the Philippines", paper presented at the 12th National Convention on Statistics, October 1-2, 2013.

Danao, R. and G. Ducanes [2016] "An error correction model for forecasting Philippine aggregate electricity consumption", *EPDP Working Paper* 2016-05. Quezon City, Philippines.

Danao, R. [2001] "Short-run demand for residential electricity in rural electric cooperatives franchise areas" *Philippine Review of Economics* 38(2): 67-82.

Dergiades, T. and L. Tsouldifis [2008] "Estimating residential demand for electricity in the United States, 1965-2006", *Energy Economics* 30: 2722-2730.

Dilaver, Z. and L. Hunt [2011] "Modeling and forecasting Turkish residential electricity demand", *Energy Policy* 39(6): 3117-3127.

Donatos, G. and G. Mergos [1991] "Residential demand for electricity: the case of Greece", *Energy Economics* 13(1): 41-47.

Enders, W. [2015] *Applied Economic Time Series*. Hoboken, New Jersey: Wiley.

Engle, R., et al. [1983] "Exogeneity", *Econometrica* 51: 277-304.

Engle, R. and C. Granger [1987] "Cointegration and error correction: representation, estimation, and testing", *Econometrica* 55(2): 251-276.

Espey, J. and M. Espey [2004] "Turning on the lights: a meta-analysis of residential electricity demand elasticities", *Journal of Agricultural and Applied Economics* 36: 65-81.

Filippini, M. and S. Pachauri [2004] "Elasticities of electricity demand in urban Indian households", *Energy Policy* 32: 429-436.

Granger, C. [1969] "Investigating causal relations by econometric models and cross-spectral methods", *Econometrica* 37(3): 424–438. doi:10.2307/1912791.

Halicioglu, F. [2007] "Residential electricity demand dynamics in Turkey", *Energy Economics* 26: 201-224.

Harris, R. [1995] *Using cointegration analysis in econometric modelling.*

Hondroyiannis [2004] "Estimating residential electricity demand for electricity in Greece", *Energy Economics* 26(3): 319-334.

Jamil, F. and E. Ahmad [2011] "Income and price elasticities of electricity demand: aggregate and sector-wise analysis", *Energy Policy* 39(9): 5519-5527.

Jorgensen, J. and F. Joutz [2012] "Modelling and forecasting residential electricity consumption in the US Mountain Region", *RPF Working Paper* No. 2012-003. Washington, DC

Navarro, A. et al. [2016] "Post-EPIRA impacts of electric power industry competition policies", *PIDS Discussion Paper* 2016-15.

Odhiambo, N. [2009] "Electricity consumption and economic growth in South Africa: a trivariate causality test", *Energy Economics* 31(5): 635 – 640.

Pesaran, M. and A. Timmerman [2002] "Market timing and return prediction under model instability", *Journal of Empirical Finance* 9: 495-510

Philippine Statistical Authority [2016] "Quarterly Gross Domestic Product Series", https://psa.gov.ph/national-accounts/base-2018/data-series. Accessed June 2016

Department of Energy [2016] "2015 Philippine Power Statistics", https://www.doe.gov.ph/2015-philippine-power-statistic?ckattempt=1. Accessed June 2016

Ravago, et al [2016] Filipino 2040 energy: power security and competitiveness. *EPDP Working Paper* 2016-01R. Quezon City, Philippines.

Stock, J. [1997] "Cointegration, long-run comovements and long-horizon forecasting", in D. Kreps and K. Wallis, eds*., Advances in econometrics: proceedings of the seventh world congress of econometric society* 3: 34-60. Cambridge, United Kingdom: Cambridge University Press.

Climatic Research Unit (University of East Anglia) and Met Office. "HadCRUT global temperature dataset", https://sites.uea.ac.uk/cru/data. Accessed June 2016

World Bank [2003] Philippines: an opening for sustained growth. *Country Economic Report* No. 11061-PH. Washington D.C., United States.

Wickham et al. [2019] "Welcome to the Tidyverse", *Journal of Open Source Software* 4(43): 1686. https://doi.org/10.21105/joss.01686.

World Bank (WB) [n.d.] "Sustainable Energy for All", https://databank.worldbank.org/reports.aspx?source=sustainable-energy-for-all. Accessed January 2016

Yohanis, Y., et al. [2008] "Real-life energy use in the UK: how occupancy and dwelling characteristics affect domestic electricity use", *Energy and Buildings* 40: 1053-1059.

Zachariadis, T. and N. Pashourtidou [2007] "Empirical analysis of electricity consumption in Cyprus", *Energy Economics* 29(2): 183-198.