Estimating Residential demand for Electricity in the United States

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Abstract

The paper examines econometric relationship between residential electricity consumption and relevant variables such as income, price of electricity and natural gas, customer characteristics as well as climatic variables. The model under this study follows with a model proposed by Chern *et al* (1988). A partial adjustment model is specified and estimated using time-series for the United States over the period 1960-1996.

The results indicate that the estimated short-run own-price elasticity for residential electricity demand is −0.213, while the long-run own-price elasticity is −0.975. The short-run and long-run income elasticities are 0.299 and 1.37, respectively. The results also show that there were significant structural changes in residential electricity demand during 1973-74. These changes can be best explained by the impact of the 1973 oil embargo. However, there was no such structural change in 1983 which it was another reversal of increasing price trend.

1. Introduction

Estimation and forecast of electricity demand have received considerable attention among economists and energy analysts in recent years. Since price and income elasticities of residential electricity demand re essential for projecting future electricity demand growth, the results from this study will help us understand how electricity demand can be managed by effectively various energy pricing and conservation policies. In addition, there are several reasons supporting the importance of estimation the demand for electricity. First, a controversial issue about economic and environmental impact from establishing electricity plant can be alleviated from detailed study done by econometricians. Secondly, it is time-consuming to construct new electricity plants. Therefore, well-before-hand estimation and forecast are needed to meet future needs for electricity. Finally, more recent interests are focused on deregulation of electricity markets utilities facing such volatile and dynamic markets need badly as dependable as possible understanding of electricity market.

The demand for residential electricity can be derived from the demand for services, such as heating, cooling and cooking, which are produced by using electric appliances. Therefore, the use of electric appliances and the stock of appliances are major determinants of the demand for residential electricity. In the short run, the intensity with which consumers use electric appliances depends on their income, the price of electricity, housing unit structure, demographic characteristics, seasonal variation and weather.

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2. Model Specification

There are various methods in forming the model of electricity demand. One method is to incorporate equipment stock directly into the model. It may be appropriate to include equipment stock directly into the measure of short-run electricity demand and distinguish between the utilization and equipment stock components in the long run, however, the problem is the availability of sufficient data. Previous studies showed that the "capital stock equations leave much to be desired" [see Branch (1993), Silk and Frederick (1997), and Smith (1980)].

Another way to model residential electricity demand is to include equipment stock indirectly. Thus we need not to bother from severe stock data problem. Suppose the actual electricity consumption in period t denoted by Y_t, while the long-run desired consumption is Y_t^*. The relevant variables affecting to electricity consumption are own-price electricity, cross-prices, income, weather conditions etc, denoted by $X_{1t}, X_{2t}, \ldots\ldots\ldots, X_{kt}$. Hence, the long-run desired consumption Y_t^* is given by a logarithmic form as:

$$\ln Y_t^* = \beta_0 + \beta_1 \ln X_{1t} + \beta_2 \ln X_{2t} + \ldots\ldots\ldots\ldots + \beta_k \ln X_{kt} + \varepsilon_t \qquad (1)$$

where ε_t is the disturbance term and assumed to be independently and identically normally distributed with zero mean and variance σ^2. The relationship between actual and desired electricity consumption is given by

$$\ln Y_t - \ln Y_{t-1} = \delta(\ln Y_t^* - \ln Y_{t-1}) + u_t \qquad (2)$$

where u_t is a random disturbance term. δ, such that $0 < \delta \leq 1$, is known as the coefficient of adjustment and where $Y_t - Y_{t-1}$ is actual change and $(\ln Y_t^* - \ln Y_{t-1})$ is desired change. Equation (2) postulates that the actual change in electricity consumption in any given time period t is some fraction δ of the desired change for that period. If $\delta = 1$, it means that actual stock adjusts to the desired stock instantaneously. If $\delta = 0$, it means that there is no adjustment.

Equation (2) can be written as:

$$\ln Y_t = \delta \ln Y_t^* + (1-\delta)\ln Y_{t-1} + u_t \qquad (3)$$

Substitution of equation (1) into equation (3) gives

$$\ln Y_t = \delta\beta_0 + (1-\delta)\ln Y_{t-1} + \delta\beta_1 \ln X_{1t} + \delta\beta_2 \ln X_{2t} + \ldots + \delta\beta_k \ln X_{kt} + v_t \qquad (4)$$

where $v_t = \delta\varepsilon_t + u_t$ representing composite disturbance term. If $\delta\varepsilon_t$ and u_t are independently and identically normally distributed, v_t is also independently and identically normally distributed.

Since equation (1) represents the long-run demand for electricity, equation (4) can be called the short-run demand for electricity. Once we estimate the short-run function in equation (5) and obtain the estimate of the adjustment coefficient δ. The long-run function can be determined by simply dividing $\delta\beta_0, \delta\beta_1, \ldots, \delta\beta_k$ by δ and omitting the lagged Y term, which will then give equation (1).

The model used in this study follows with a model proposed by Chern *et al* (1988). It is a partial adjustment model which residential demand for electricity is expressed as a function of the lagged demand and other demand determinants. A dynamic model is specified and estimated by using pooled time series data in the U.S. over the period 1960-1996.

$$\begin{aligned}\ln E_t &= \beta_0 + \beta_1 \ln E_{t-1} + \beta_2 \ln PE_t + \beta_3 \ln PCI_t + \beta_4 \ln CR_t \\ &\quad + \beta_5 \ln POPCR_t + \beta_6 \ln HDD_t + \beta_7 \ln CDD_t + \beta_8 \ln PG_t + v_t\end{aligned} \tag{5}$$

where t = year (t = 1960-1996); E = residential electricity consumption; PE = real electricity price in the residential sector; PCI = real per capita personal income; CR = number of residential electricity customers; $POPCR$ = household size measured by dividing population by the number of residential customers; HDD = heating degree days; CDD = cooling degree days; PG = real natural gas price in the residential sector; v_t = disturbance term.

2.1. Interpretation of coefficients

- β_0 = the estimated coefficient of constant term; β_1 = the estimated coefficients of the lagged dependent variables. $(1-\beta_1)$ = the coefficient of adjustment which measures how fast the response to exogenous changes takes place. The larger the coefficient estimate, β_1, the slower the adjustment. In a partial adjustment model for energy demand, dynamic behavior is explained by changes in durable stock. For a more durable appliance, it takes longer to wear out the existing stock. Therefore, the speed of adjustment is lower; β_2 = the estimated short run own price elasticity and $\beta_2/(1-\beta_1)$ = the estimated long run own price elasticity; β_3 = the estimated short run income elasticity; β_4 = the estimated short run customer elasticity. The customer elasticities measure the effects on demand due to the addition of new customer; β_5 = the estimated short run household size elasticity; β_6 , β_7 = the estimated short run climatic elasticity, heating degree days and cooling degree days, respectively; β_8 = the estimated short run cross-price elasticity.

3. Data Sources

The units of variables and data sources are used in this study shown in *Table 1*. The prices of electricity and natural gas are measured in nominal term without taking account into inflation rate. Thus, the real prices of electricity and natural gas are calculated by dividing the nominal prices by the consumer price index (1992=100). The data of residential electricity consumption are obtained from the categories of annual electricity sales in U.S. residential sector. The data for per capita disposable income are measured in 1992 constant dollar.

Table1 : The units of variables and data sources used in the study

Variables	Units	Sources
Residential electricity prices	*dollar per MBtu*	EIA[1] WebPages
Residential natural gas prices	*dollar per MBtu*	EIA WebPages
Residential electricity consumption	*million per kWh*	EIA WebPages
Per capita personal income	*dollar per capita*	Economic Report of President, 1998
Population	*total*	Statistical Abstract of the United States
Consumer price index	*index*	Economic Report of President, 1998
Number of residential electricity customers	*total*	EEI[2] Statistical Yearbook
Heating degree days	*days*	EIA WebPages
Cooling degree days	*days*	EIA WebPages

[1] Energy Information Administration (www.eia.doe.gov)
[2] Edison Electricity Institute (www.eei.org)

4. Empirical studies and Results

4.1 The Unit Root Test of Stationarity and Test for Cointegration

The model of residential electricity demand defined in equation (5) has used time series data in the U.S. over the period 1960-1996. Regression analysis based on time series data implicitly assumes the underlying time series are stationary. Therefore, the classical *t* tests, *F* tests, etc. are based on this assumption. In practice, most economic time series are nonstationary. If we have regressed one nonstationary time series on another nonstationary time series, in such a case the standard *t* and *F* testing procedures are not valid. In this sense, the estimated regression suffers from spurious regression. One way to guard against it is to find out whether the time series are integrated or not. Cointegration means that despite being individually nonstationary, a linear combination of two or more time series can be stationary where there is a long-run, or equilibrium, relationship between them. As this result, the classical *t* tests, *F* tests, etc are still valid.

The paper begins with the unit root test for stationary known as "Dickey-Fuller" (DF) test that can be formed as

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t \qquad (6)$$

where t is the time or trend variable; $\Delta Y_t = (Y_t - Y_{t-1})$ or the first differences of a variable Y_t; u_t is the stochastic error term. The null hypothesis is that $\delta = 0$, that is, there is a unit root.

If the error term u_t is autocorrelated, one uses the Augmented Dickey-Fuller (ADF) test as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + u_t \qquad (7)$$

where $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$, etc, that is, one uses lagged difference terms.

Table A shows the results from the unit root test for stationary or Dickey-Fuller (DF) test

Variable	Computed Test-statistic	Critical value Lower tail area	Conclusion
E	-1.879	0.682	*Nonstationary*
PE	-1.818	0.710	*Nonstationary**
PCI	-1.901	0.671	*Nonstationary*
CR	-2.330	0.440	*Nonstationary**
POPCR	1.612	0.999	*Nonstationary**
HDD	-4.459	0.006	*Stationary*
CDD	-7.432	0.000	*Stationary*
PG	-0.740	0.964	*Nonstationary**

Note : * The *h*-Durbin test statistic values on *PE, CR, POPCR, PG* show the serial correlation in u_t.

Table B indicates the results from the Augmented Dickey-Fuller (ADF) test

Variable	Computed Test-statistic	Critical value Lower tail area	Conclusion
PE	-2.383	0.412	*Nonstationary*
CR	-1.358	0.872	*Nonstationary*
POPCR	2.072	0.999	*Nonstationary*
PG	-1.096	0.924	*Nonstationary*

The DF test indicates that the computed test statistic value of *E, PE, PCI, CR, POPCR, PG* are –1.879, -1.818, -1.901, -2.330, 1.612, -0.740, respectively, which in absolute terms are smaller than 5% critical value. Therefore, we do not reject the null hypothesis that δ = 0, that is, the *E, PE, PCI, CR, POPCR, PG* series are nonstationary. However, the *h*-Durbin test statistic values of *PE, CR, POPCR, PG* show the serial correlation in u_t. Therefore, the ADF test is applied to test on *PE, CR, POPCR, and PG*. *Table B* shows that the computed test statistic values of *PE, CR, POPCR, PG* are –2.383, -1.358, 2.072, and –1.096, respectively, which in absolute terms are smaller than 5% critical value suggesting that the *PE, CR, POPCR* and *PG* time series are nonstationary. On the other hand, the DF test on *HDD* and *CDD* in *Table A* indicates that the computed test statistic values of *HDD, CDD* are –4.459, -7.432, respectively, which in absolute terms are greater than 5% critical value. Therefore, the *HDD, CDD* series do not exhibit a unit root, or say, the *HDD* and *CDD* series are stationary.

Table C indicates the results from test of cointegration

Variable	Computed Test-statistic	Critical value Lower tail area	Conclusion
Res(-1)	-5.981	0.000	*Cointegration*

Table C shows that the test for cointegration by regressing equation (5) and subjecting the residuals estimated from this regression to the DF unit root test. The computed test statistic value is –5.981, which in absolute term is greater than 5% critical value. The conclusion would be that the estimated residual is stationary, and, therefore there is cointegrated or a long-run, or equilibrium, relationship between variables in equation (5). Hence, the classical *t* test, *F* test, etc are valid and applicable for testing pooled time series data in equation (5)

4.2 Estimation Methods for Partial Adjustment Model

Equation (5) is in the form of partial adjustment model. In this model, $v_t = \delta u_t$, where $0 < \delta \leq 1$. Hence, if u_t satisfies the assumption of the classical linear regression model, so will δu_t. Thus, OLS estimation of the partial adjustment model will yield consistent estimates although the estimates tend to be biased (in finite or small samples). The underlying reason is even Y_{t-1} depends on u_{t-1} and all previous disturbance terms, it is not related to the current error term u_t. Therefore, as long as u_t is serially independent, Y_{t-1} will also be independent or at least uncorrelated with u_t, thereby satisfying an important assumption of OLS. If v_t is autocorrelated, then the OLS estimate would be inconsistent and biased.

The study will test whether v_t is autocorrelated or not. If there is no autocorrelation between disturbance terms, the OLS estimates is consistent and asymptotically efficient.

4.3 OLS Estimation

The study begins with a classical estimation of OLS method. The results from OLS estimation are displayed in *Table 2*. Overall, the results are quite encouraging. The R^2 and adjusted R^2 in the estimated equation (5) are 0.99945 and 0.99929, respectively. The *F*-statistic of the model is very high with 6240.236. Hence, all explanatory variables included in the model are well explained to electricity consumption. Since the equation (5) is partial adjustment model including lagged dependent variable, the traditional Durbin-Watson test can not be tested to examine the autocorrelation problem. The test for autocorrelation problem will be studied in the following section.

Table 2 : The OLS estimation results

Valid cases:	36	Dependent variable:	*E*
Total SS:	7.686	Degrees of freedom:	27
R-squared:	0.99945	Rbar-squared:	0.99929
Residual SS:	0.004	Std error of est:	0.012
F(8,27):	6240.236	Probability of F:	0.000
Durbin-Watson:	2.058		

Variable	Estimate	Standard Error	Prob t-value
Const	*-5.497352*	*5.237138*	*-1.025419*
Elag	*0.801311*	*0.049606*	*16.153468*
PE	*-0.181456*	*0.096273*	*-2.884806*
PCI	*0.356392*	*0.162284*	*2.196104*
CR	*0.116428*	*0.219546*	*2.530313*
POPCR	*0.456240*	*0.685103*	*0.665944*
HDD	*0.176396*	*0.057880*	*3.047611*
CDD	*0.208366*	*0.042126*	*4.946258*
PG	*0.057434*	*0.037767*	*2.120760*

All the explanatory variable coefficients are of the expected signs and are plausible. All coefficient estimates except price of electricity and constant term are positive. In addition, the *t*-statistics of all coefficient estimates except constant term and household size variable are significant at the level 0.05. The adjustment rate, $(1-\beta_1)$, which measures how fast the response to exogenous changes takes place, is 0.1987, (1-0.8013). The larger the coefficient estimate β_1, the slower the adjustment speed. The coefficient of own-price elasticity, which is measured as the short-run own-price elasticity, is −0.1814 with the *t*-statistic of −2.884. The long-run own-price elasticity, which is measured by dividing short-run elasticity by the adjustment rate, is −0.913, (-0.1814/0.1987).

The coefficient of the cross-price elasticity (by natural gas), which measures the short-run cross-price elasticity, is 0.057 with statistically significant at the level 0.05. The long run cross-price elasticity is 0.287 (0.057/0.1987). The short-run income elasticity is 0.356 with statistically significant at the level 0.05. The long-run income elasticity is 1.792 (0.356/0.1987). The coefficients of the two climatic variables, heating and cooling degree-days, are positive and statistically significant at the level 0.05. The coefficient of number of customers is 0.116 with the significance at the level 0.05 but the coefficient of household size is 0.456 and statistically insignificant.

Overall, the OLS results are quite encouraging. However, the further tests are required to attain the purpose of most efficient estimation.

5. Test for Autocorrelation for Lagged Dependent Variable

Since the estimated equation (5) is a lagged dependent variable, the Durbin-Watson *d* statistic may not be used to detect first-order serial correlation. Therefore, we need the Durbin's *h*-statistic in order to detect first-order serial correlation in autoregressive models.

$$h = (1 - 0.5d)\sqrt{\frac{n}{1 - n\left[\text{var}(\alpha_2)\right]}}$$

where n = sample size; var(α_2) = variance of the coefficient of the lagged Y_{t-1}; d = the usual Durbin-Watson statistic.

The study shows that $h = (1 - 0.5 * 2.058)\sqrt{\frac{36}{1 - 36\left[0.0496^2\right]}} = -0.1831$

The absolute value of Durbin's h-statistic is less than the critical value of 1.96. Therefore, there is no first-order serial correlation. As this result, the OLS estimator is still unbiased and efficient.

6. Test for Heteroscedasticity Problems

The heteroscedasticity will occur when the disturbance is not constant across observation, that is $E(e_i^2) = Var(e_i) = \sigma_i^2$. In general, the heteroscedasticity will arise with primarily cross sectional data but it occurs less common with time series data. The heteroscedasticity will cause OLS estimator inefficient but remains unbiased.

There are many methods in detecting the heteroscedasticity problem. The paper will compare and test the problem by using the techniques of White Test, Breusch-Pagan/Godfrey Test, Goldfeld-Quandt Test and Glester Test. The results of the tests for heteroscedasticity problem indicate in *Table 3.*

The White test, Breusch-Pagan/Godfrey test and Glesjer test indicate that the test statistic does not exceed the critical value. Therefore, the null hypothesis is accepted under 5% critical level of significant meaning that there is no heteroscedasticity. However, Goldfeld-Quandt test, which data are sorted by *PE, PG* and *CDD* shows the heteroscedasticity problem because the test-statistic is greater than critical value at 5% level of significant. As this result, the OLS estimators from part B are no longer efficient.

The degrees of freedom of Goldfeld Quandt test, which data are sorted by *PE, PCI, CR, POPCR* and *PG,* are five because the tests take the first and last fourteen observations to run regression. On the other hand, the degree of freedom from data sorted by *HDD* and *CDD* is one because the first and last ten observations are run regression with K = 9 (including constant term) to avoid positive singular matrix problems.

Table 3 compares the test results from using different methods.

Method	Test-Statistic	Critical Value	Conclusion
(1) White Test *(auxiliary regression)*	$TR^2 = 30.7935$	$\chi^2(k\text{-}1,\alpha)$ $\chi^2(29,0.05) = 42.5569$	No heteroscedasticity
(2) Breusch-Pagan Test *(Lagrange multiplier)* $\sigma^2 = \sigma^2 f(\alpha_0 + \alpha Z)$	$\theta = 0.5{*}ESS = 8.7837$	$\chi^2(8,0.05) = 15.5073$	No heteroscedasticity
(3) Glesjer Test *(Lagrange multiplier)*	*Wald Test*		
a) $Var(\varepsilon) = \sigma^2[\alpha Z]$	$W_1 = 9.08217$	$\chi^2(8,0.05) = 15.5073$	No heteroscedasticity
b) $Var(\varepsilon) = \sigma^2[\alpha Z]^2$	$W_2 = 13.4384$	$\chi^2(8,0.05) = 15.5073$	No heteroscedasticity
c) $Var(\varepsilon) = \sigma^2\exp[\alpha Z]$	$W_3 = 11.0683$	$\chi^2(8,0.05) = 15.5073$	No heteroscedasticity
(4) Goldfeld-Quandt *Data sort by*	$F = RSS_1/RSS_2$	$F((T\text{-}C\text{-}2K)/2,(T\text{-}C2K)/2)$	
a) PE	$F = (613.507/120.624) = 5.0861$	$F(5,5,0.05) = 5.05$	Heteroscedasticity
b) PCI	$F = (318.113/106.544) = 2.985$	$F(5,5,0.05) = 5.05$	No heteroscedasticity
c) CR	$F = (318.577/205.710) = 1.548$	$F(5,5,0.05) = 5.05$	No heteroscedasticity
d) POPCR	$F = (219.820/109.764) = 2.002$	$F(5,5,0.05) = 5.05$	No heteroscedasticity
e) HDD	$F = (0.00885/0.00349) = 2.643$	$F(1,1,0.05) = 161$	No heteroscedasticity
f) CDD	$F = (1.543/0.00073) = 2105.54$	$F(1,1,0.05) = 161$	Heteroscedasticity
g) PG	$F = (1239.89/220.315) = 7.897$	$F(5,5,0.05) = 5.05$	Heteroscedasticity

7. GLS Estimation

Since heteroscedasticity does not destroy the unbiasness and consistent properties of OLS estimator, but they are no longer efficient, not even asymptotically with large sample size. This lack of efficiency makes the usual hypothesis-testing procedure of dubious value. The paper will obtain the GLS estimation to remedy the sources of heteroscedasticity problem. The GLS estimation with known Ω, has $\beta^{GLS} = \left(X'\Omega^{-1}X\right)^{-1} X'\Omega^{-1}y$ and assumes $Var(e_i) = \sigma_i^2 = \sigma_e^2 w_i$. The transformation of data is divided through regressor and regressand by $\sqrt{w_i}$.

Table 4 *indicates the results from GLS estimation and compares with OLS estimation.*

Valid cases:	36	Durbin-Watson:	1.914
Total SS:	4.886	Degrees of freedom:	27
R-squared:	1.000	Rbar-squared:	1.000
Residual SS:	0.008	Std error of est:	0.010
F(9,27):	6890.632	Probability of F:	0.000

Variable	**Estimate**			**Standard**	**Prob**
	GLS	**OLS**	***diff***	**Error**	**t-value**
Const	***-5.454002***	*-5.497352*	*0.043350*	*5.106663*	*-1.241120*
Elag	***0.781600***	*0.801311*	*-0.019711*	*0.011270*	*26.59543*
PE	***-0.213015***	*-0.181456*	*-0.031559*	*0.027771*	*-4.320612*
PCI	***0.299643***	*0.356392*	*-0.056749*	*0.050731*	*2.242843*
CR	***0.178070***	*0.116428*	*0.061642*	*0.060060*	*2.126330*
POPCR	***0.547853***	*0.456240*	*0.091613*	*0.203902*	*1.030307*
HDD	***0.174889***	*0.176396*	*0.001507*	*0.011681*	*2.158401*
CDD	***0.212300***	*0.208366*	*0.003934*	*0.018040*	*4.133638*
PG	***0.065216***	*0.057434*	*0.007782*	*0.007157*	*2.905766*

Overall, the coefficients from GLS estimation are of the expected signs, plausible and have similar representations with the OLS equation. The difference of coefficients from GLS and OLS estimation is also shown in the *Table 4*. In the presence of heteroscedasticity in the model, the OLS estimators are no longer efficient, not even asymptotically (i.e., large sample size). This lack of efficiency makes the usual hypothesis-testing procedure of dubious value. Therefore, the GLS estimators are more effective and reliable than the OLS estimators. The paper will apply the results obtained from the GLS estimation.

Table 5 : The GLS results compare with 2SLS results by Chern (1988)

Estimated coefficients of variables	**Supawat (2000) GLS estimation 1960-1996**	**Chern *et al.* (1988) 2SLS estimation 1955-1978**
Elag	0.782	0.842
PE	-0.213	-0.115
PCI	0.299	0.135
CR	0.178	0.176
POPCR	0.547	0.064
HDD	0.174	0.103
CDD	0.212	0.032
PG	0.065	0.010
R^2	*1.000*	*0.999*

Table 5 demonstrates the comparisons of the GLS results from this study with the 2SLS results by Chern *et al* (1988). Overall, the coefficients from GLS estimation have the same signs as the previous study done by Chern *et al*. The paper follows the model by Chern *et al* and extends the time period through 1996. The results are consistent with the study by Chern *et al*. Among the studies recently compiled and reviewed by Bohi (1982), the estimated short-run price elasticities for residential electricity demand range from –0.03 to –0.54 while the long-run elasticities estimates range from –0.44 to –2.10. For income elasticities, the short-run estimates range from 0.02 to 2.0 with the long-run estimates ranging from 0.12 to 2.20. The short-run and long-run price (income) elasticities from this study are also consistent with the previous studies.

8. Test for Structural Change

The paper further investigates the stability of the structural changes in residential electricity demand. There are two underlying sources for a possible structural change. First, consumers may react differently to declining and rising prices. Secondly, the significant increases of oil price in 1973-74 and 1983-84 may have shifted demand preferences. As this result, the paper will examine whether there will be shifts in residential electricity demand structure in the U.S.

The paper tests such structural changes by obtaining the Chow Test. The basic idea is a structural change or structural break occurs if the parameters underlying a relationship differ from one subset of the data to another.

The assumptions underlying the Chow test are twofold;

(a) $u_{1t} \sim N(0,\sigma^2)$ and $u_{2t} \sim N(0,\sigma^2)$

that is, the two error terms are normally distributed with the same variance, σ^2 and

(b) u_{1t} and u_{2t} are independently distributed

Given the assumptions of the Chow test, it can be shown that

$$F = \frac{S_5 / k+1}{S_4 / (n_1 + n_2 - 2k - 2)}$$

Follows the F distribution with $df = (k+1,\ n_1+n_2-2k-2)$, where k = number of explanatory variables; $S_5 = S_1 - S_4$ and $S_4 = S_2 + S_3$; S_1 is residual sum of squares of the whole observation; S_2 is residual sum of squares of the first group, n_1; S_3 is residual sum of squares of the second group, n_2.

The paper tests two plausible structural changes in 1973 and 1983. The first possible structural change in 1973 is tested by dividing the sample into two subsets of 1960-1972 and 1973-1996. With another possible structural change in 1983, the sample will be divided by two subsets of 1960-83 and 1984-96.

Table 6 shows the results of test for structural change by using the Chow test.

RSS	Test Statistic	Critical Value	Conclusion
(1) *Test for structural change in 1973* RSS_1 (1960-96) = 0.0041548 RSS_2 (1960-72) = 0.0000294 RSS_3 (1973-96) = 0.0008982	F = 6.9577	F(9,16,0.05) = 3.01	*There is structural change*
(2) *Test for structural change in 1983* RSS_1 (1960-96) = 0.0041548 RSS_2 (1960-83) = 0.0024570 RSS_3 (1984-96) = 0.0024898	F = 1.0707	F(9,16,0.05) = 3.01	*There is no structural change*

The results of *Table 6* indicate that the null hypothesis of no structural change is rejected under 5% critical levels for the test of structural change in 1973. Therefore, the reversal of price trend resulting from the 1973 oil embargo results to the structural changes in residential electricity demand. However, the null hypothesis of no structural change is accepted under 5% critical levels for the test of structural change in 1983. Therefore, there is no such structural change in residential electricity demand under this period.

(6) Interpretation and Conclusion

The final estimation of equation 5 which is obtained by the GLS method is given as follow (with *t*-statistic in the parenthesis):

$$\ln E_t = -5.454002 + 0.7816 \ln E_{t-1} - 0.213015 \ln PE_t + 0.299643 \ln PCI_t + 0.17807 \ln CR_t$$
$$(-1.241) \quad (26.595) \quad (-4.3206) \quad (2.2428) \quad (2.1263)$$
$$+ 0.547853 \ln POPCR_t + 0.174889 \ln HDD_t + 0.2123 \ln CDD_t + 0.065216 \ln PG_t$$
$$(1.0303) \quad (2.1584) \quad (4.133) \quad (2.905)$$

- ***Estimated coefficients for the lagged dependent variable***

The estimated coefficient of the lagged dependent variable, β_1, in equation (5) is 0.7816. The coefficient of adjustment, ($1-\beta_1$), measures how fast the response to exogenous changes takes place. The larger the coefficient estimate, β_1, the slower the adjustment. We can explain the rate of adjustment in terms of changes in durable stock. For a more durable appliance, it takes longer to wear out the existing stock. The study shows the adjustment rate is 0.2184.

- ***Own-price elasticity***

The study shows the short-run own-price elasticity, β_2, is –0.213 and the long-run own price elasticity calculated by dividing short-run elasticity by $(1-\beta_1)$, is –0.975. Therefore, the one percent increase in electricity price would decrease on electricity demand by 0.213% in the short-run while it would decrease by 0.975% in the long-run.

- ***Income elasticity***

The estimated income coefficient (short-run elasticity), β_3, is 0.2996 and the long-run income elasticity, $\beta_3/(1-\beta_1)$, is 1.37. The one percent increase on income would increase by 0.2996% on electricity demand in the short-run and it would increase by 1.37% in the long-run.

- ***Customer coefficient***

The estimated short-run and long-run elasticities with respect to the number of residential are 0.178 and 0.815, respectively. The customer elasticities measure the effects on demand due to the addition of new customers. The elasticities are below one, indicating that new customers always have smaller average electricity consumption than existing customers.

- ***Household size***

The estimated coefficient of household size is positive and statistically insignificant at the level 0.05. As this result, the large households and small households do not affect much on their purchasing behaviors of electric appliances under the study.

- ***Climatic variables***

The estimated coefficients both heating and cooling degree-days variables are positive and have statistically significant. These results point out the obvious trend of increased usage of electricity for space heating and cooling.

- ***Cross- price effects***

The natural gas prices included in the model are considered due to the effects of interfuel substitution. When the prices of natural gas increase, these would encourage people to consume less natural gas for heating, etc in purpose and people will substitute electricity for natural gas. The short-run cross-price elasticity is 0.065 and statistically significant at the level 0.05. The coefficient is quite low implying that there is little tendency to substitute between these fuels and natural gas does not have much effect on electricity consumption under the study.

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ตำบล... อำเภอ/เขต..

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(กรุณาส่งเช็คหรือธนาณัติ สั่งจ่ายในนาม นางสินีนาฏ ธรรมณี)