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Residential Electricity Demand in Seattle

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Abstract

This study examines residential electricity demand for the Seattle City Light (SCL) public utility market. SCL is interesting because all of its electricity is generated through hydro-electric facilities as well as its purchased power, mostly through contracts with the Bonneville Power Administration, resulting in below-average residential electricity prices. An error-correction model is estimated using annual time series data. Income, price, and climate data are used to identify both economic and seasonal effects. In addition, a customer equation is also estimated using the error-correction approach. The income-elasticity is negative indicating that electricity is an inferior good in this market. Out-of-sample forecasts are generated using compound annual growth rates.

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I. Introduction

The Pacific Northwest metropolis of Seattle is the economic fulcrum of King County, and is the center of entertainment and employment for citizens located in parts of Snohomish, Pierce and Kitsap Counties. Lying on an isthmus between Puget Sound and Lake Washington, Seattle is an economic hub for trade, tourism and technology. Seattle City Light (SCL) is a public electric utility that provides service to the following cities and areas: Burien, Lake Forest Park, Normandy Park, Renton, SeaTac, Seattle, Shoreline, Tukwila, First Hill and University District. A public monopoly, SCL is the sole provider of electricity in this market and is part of the Seattle city government.

The King County population estimate for 2007 is 1,861,300 residents. From 1960 through 2007, King County per capita income increased from $4,812 at a compound annual growth rate of 5.43 percent to $57,710. The 2007 unemployment rate for King County was 3.8 percent. In 2007 the median price for existing houses was $284,996.

The number of SCL customers in 2007 was 343,542, an increase of 39 percent since 1960. This market growth has resulted in significant off-system power purchases. Total electricity consumption in 2007 reached 3,103,550,000 kilowatt hours (KWH) for that year. From 1960 through 2007 the SCL average price per KWH increased from $0.00965 to $0.0632.

The goal of this paper is to develop an econometric model for electricity demand for Seattle and the rest of the SCL service area. SCL is interesting because its market area is fixed and nearly all of its energy is generated by hydroelectric power facilities. A variety of data are utilized to attempt this endeavor.

Subsequent sections are as follows. A review of related literature is next. Section 3 discusses data and methodology. Model estimation and simulation results are then summarized.

A concluding section with suggestions for future research is next. A data appendix is included at the end of study.

II. Literature Review

Early work in residential electricity consumption (REC) theorized that inclusion of either marginal price or average price in the absence of the other will generate biased estimates and falsely identify the customer's response. The marginal rate is determined by the utility supplier over specific quantities or blocks. Taylor (1975) argues that both average price and marginal price should be included in econometric electricity demand studies to capture income and substitution effects, respectively.

Due to the differing marginal rates among various electricity suppliers, the line that differentiates these price metrics becomes less critical (Fisher and Kaysen, 1962). Cicchetti and Smith (1975) contend that econometric demand equations are simply approximations of a more complex structure. Numerous REC estimations rely on average price largely due to data constraints.

Fisher and Kaysen (1962) utilize average price for their cross sectional time study of the 48 contiguous states. Anderson (1972) models REC for California using average price. Both studies indicate that decreases in electricity consumption as a response to increases in average price are less than proportional. That is in contrast to Halvorsen (1972) which reports a negative one-to-one correlation between quantity demanded and average price.

An REC model that includes both price metrics is estimated for a southwest regional utility in Roth (1981). In this southwest area study, the intra-marginal (average) price coefficient is positive. This result is in stark contrast with the other literature. The positive coefficient estimate for the average price variable, representing a reduction in real income, indicates that electricity is an inferior good for the market in question. This is an intriguing result because it implies that higher income levels will not lead to greater electricity consumption by residential customers. Contreras (2007) reports a similar result using national data on REC and attributes it to increased energy efficiency of home appliances.

Maddigan et al. (1983) estimate rural REC with an average price equation. The dependent variable is specified as the difference between average price and average cost. Key explanatory variables are as follows: 1) quantity demanded to customer ratio, 2) a quadratic term of the ratio, 3) the number of customers, 4) a time-specific dummy, and 5) a regional dummy. The price equation is created in an attempt to maintain consistency between total average revenue and average cost and, more importantly, demonstrates an effective way to adjust for endogeneity associated with the inclusion of average price. The price elasticities exhibit negative relationships between average price and quantity demanded. Those results are consistent with other findings (Fisher and Kaysen, 1962; Wilson, 1971; Anderson, 1972). The use of the price equation also helps generate better forecasting results than those for a benchmark unconstrained price model.

Recent research has pointed to several shortcomings in the Taylor (1975) approach to marginal price questions. Among them, a problem arises with the assumption that consumers perfectly optimize utility, or more explicitly stated, respond instantaneously to changes in marginal price. Such a perfectly informed customer is rare and unrealistic. Consumers do not respond directly to a change in marginal price, but rather the price received at the end of the billing period. Such an assumption does not properly reflect consumer response to a changing block-rate (Borenstein, 2009).

To further evaluate metropolitan utility consumption patterns, results from municipal water studies may be useful. Nieswiadomy and Molina (1989) estimate residential water consumption for Denton, Texas under two different estimation periods. Customers are faced with decreasing block rates under the first period and increasing rates under the second period. Instrumental variables (IV), ordinary least squares (OLS), and two-stage least squares (2SLS) methods are used in this study. The IV and 2SLS are selected due to simultaneity bias produced by the block-rate structure data. Both decreasing and increasing block rate structures demonstrate positive income elasticities and negative price elasticities under all estimation techniques utilized.

A variety of time series approaches have also been applied in REC studies. Error-correction models (ECM) have been employed in several recent efforts (Halicioglu, 2007; Zachariadis and Pashourtidou, 2007; Dergiades and Tsoulfidis, 2008). ECMs establish a long-run equilibrium relationship by introducing past short-run disequilibria as an explanatory variable of the dynamic behavior of current variables (Maddala and Kim, 1998). ECMs offer much promise, but have fairly substantial data requirements associated with them.

Some recent studies utilize autoregressive distributed lag techniques to estimate long run elasticities. Advantages of an ARDL include avoidances of endogeneity problems and good small sample properties (Hacioglu, 2007). Hacioglu uses an ARDL model for residential demand in Turkey. Long run income elasticities range between 0.49 and 0.70 under different lag selection criteria.

Other studies include Narayan, et al's (2007) estimate of a time series cross-sectional study for the G7 countries. Of the seven countries, only Italy and Japan resulted in negative income elasticities that are less than unity, in absolute terms. Positive own-price elasticities are estimated for Italy, the United Kingdom, and the United States in this study. In Dergiades and Tsoulfidis's (2008) study of the United States, long run results indicate that increases in real per capita income generate small increases in electricity consumption, with an elasticity of only

0.278. In contrast, an increase in price leads to significant drops in end-use consumption with an elasticity coefficient equal to -1.065.

Climatic changes foster important seasonal fluctuations in demand. Commonly employed weather variables are: 1) Heating degree days, 2) Cooling degree days, and 3) mean temperature (Narayan et al, 2007; Zachariadis, et al, 2007; Lam, et al., 2008; Wangpattarapong, et al, 2008; et al). Filippini (1995) uses heating degree days (HDD) in a time-of-use residential demand study for Switzerland. Because Switzerland is a cold climate country with moderate summer temperatures, cooling degree days (CDD) is omitted from the model. During peak hours of demand, heating degree days contributes to a 0.16 percent increase in end-use consumption. The elasticity coefficient for HDD during off-peak periods is 0.75.

Other studies measure climate fluctuations as the sum of HDD and CDD. Any movement away from the baseline temperature will increase the need for heating or cooling. Narayan and Smyth (2005) perform a study of Australia in which total degree days (DD) are found to increase consumption by 1.69 percent. Zachariadis and Pashourtidou (2007) also use aggregate degree days for their REC study of Cyprus, but estimate an elasticity coefficient of only 0.209. Wangpattarapong et al. (2008) analyze the impact of climatic and economic factors on REC for Bangkok. The income coefficient is below the 95 percent significance level and is dropped from the model. Whether that surprising outcome applies to other markets remains to be seen.

Seattle, a major metropolitan area is one of the more unique electricity markets in the United States. SCL, Seattle's sole electricity service provider is a public utility that generates electricity through its hydroelectric plants. Its primary off-system purchases are through contracts with the Bonneville Power Administration, another hydroelectricity provider. This method of generation has translated into low electricity prices for consumers. In effect, consumers in the Seattle market may be indifferent to price changes. This is important when considering the findings of Roth (1981) and Contreras (2007) that electricity is an inferior good. Econometric analysis of REC in Seattle may shed light on this possibility.

III. Data and Methodology

The primary data for analysis come from SCL annual reports. The statistical information is from 1960 to 2007. Consumption data include total residential consumption and the number of customers. Revenue statistics include total revenue, average revenue per customer, and average revenue per kilowatt hour. Average revenue per kilowatt hour is used as the price variable.

Per capita income is used to account for cyclical economic influences on electricity consumption. Per capita income data for Seattle are reported by two different agencies: 1) Bureau of Economic Analysis (BEA) and, 2) Washington State Employment Security Department (WSESD). The WSESD reports county data, and the BEA reports surrounding metropolitan statistical area (SMSA) data. Fortunately, SCL collects income and other economic data specific to its market area. The SCL data are used in the analysis since they provide a more accurate gauge of economic conditions for the service area. The Seattle consumer price index from the U.S. Bureau of Labor Statistics is used to deflate the price and income data.

Under the SCL current pricing structure, the block rates for residential customers are increasing. This rate varies among different cities within the service area because the cost to provide electricity is not uniform across the market. Because SCL is a public utility, rates must be set so that no one area subsidizes another. Secondly, rates are set up solely to cover the cost of producing electricity. This decision rule differs from a private utility service provider where profit maximization is sought. Data constraints prevent estimation of marginal price tariffs.

Electricity consumption is consumed through surrogates of appliances, heaters, televisions, and other electricity using durables. Heaters and air conditioners are used to relieve seasonal weather conditions and can increase the amount of electricity consumption for a given household. Stock data for these consumables are lacking. As a result, proxies must be used to account for stock durables and seasonal fluctuations.

The number of customers will be used to account for the stock of consumer durables. As the number of customers increase, the need to obtain household electrical goods for everyday living will rise (Dergiades and Tsoulfidis, 2008). Customers are equal to the number of meters billed by the utility. Seasonal effects account for increases in heating and cooling system use.

Seattle is a cold weather city and has low summer temperatures. Dating back to 1960, the average temperature of the summer months of June, July and August has not reached 70 degrees Fahrenheit. This figure is calculated using the average monthly temperatures for June, July, and August provided by the Western Regional Climate Center (WRCC). This was done for every year between 1960 and 2007, and does not result in any value greater than 69.5 degrees. As a result, cooling degree days is not included in any subsequent estimation.

Heating degree days data are reported by the WRCC and are used as a surrogate for seasonal increases in heating systems use (Fillippini, 1995; Dergiades and Tsoulfidis, 2008). The general model for residential electricity demand is as follows: KWH = f (P, Y, CSTM, HDD), where P is the average price per kilowatt hour, Y is personal income, CSTM is the number of customers, and HDD is heating degree days. Long-run consumption per customer is specified in Equation 1, where α_0 is the drift term, YCAP is per capita income and u_t is the disturbance term.

$$\mathrm{Ln}(KWH_t/CSTM_t) = \alpha_0 + \underset{(+)}{\alpha_1 \mathrm{Ln}YCAPt} + \underset{(-)}{\alpha_2 \mathrm{Ln}P_t} + \underset{(+)}{\alpha_3 \mathrm{Ln}HDD_t} + u_t \qquad (1)$$

Per capita income is expected to increase consumption because increases in disposable income are expected to increase purchases and usage of electricity using goods (Silk and Joutz, 1997).

However, as Roth (1981) and Contreras et al. (2009) have shown, electricity, in some markets, may be an inferior good. The price coefficient is expected to be negative as increases in price will lead to a reduction in the consumption of a good or service. HDD is expected to have a positive sign because deviations below the baseline temperature (65^{o} F) increase the need for heating (Dergiades and Tsoulfidis, 2008).

Beyond the long-run relationship shown in Equation 1, it may be helpful to also examine short-run characteristics of residential electricity consumption.

$$dLn(KWH_t/CSTM_t) = b_0 + \underset{(+)}{b_1 dLnYCAP_t} + \underset{(-)}{b_2 dLnP_t} + \underset{(+)}{b_3 dLnHDD_t} + \underset{(-)}{b_4 u_{t-1}} + v_t \qquad (2)$$

where:

$dLnYCAP_t$ is the differenced log income term
$dLnP_t$ is the differenced log price term
$dLnHDD_t$ is the differenced log heating degree days term
u_{t-1} is the error correction term
v_t is a random disturbance term

An expression for the error-correction variable can be extracted from the long run equation at lag t-1.

$$u_{t-1} = Ln(KWH_{t-1}/CSTM_{t-1}) - \alpha_0 - \alpha_1 LnYCAP_{t-1} - \alpha_2 LnP_{t-1} - \alpha_3 LnHDD_{t-1} \qquad (3)$$

Substitution of Equation 3 into Equation 2 yields a new expression in Equation 4.

$$dLn(KWH_t/CSTM_t) = b_0 + b_1 dLnYCAP_t + b_2 dLnP_t + b_3 dLnHDD_t + b_4[Ln(KWH_{t-1}/CSTM_{t-1})$$

$$- \alpha_0 - \alpha_1 LnYCAP_{t-1} - \alpha_2 LnP_{t-1} - \alpha_3 LnHDD_{t-1}] + v_t \qquad (4)$$

Multiplying coefficient b_4 throughout the bracketed terms, and combining the constant terms, leads to the specification in Equation 5.

$$dLn(KWH_t/CSTM_t) = [b_0 - b_4\alpha_0] + \underset{(+)}{b_1 dLnYCAP_t} + \underset{(-)}{b_2 dLnP_t} + \underset{(+)}{b_3 dLnHDD_t} +$$
$$\underset{(-)}{b_4 Ln(KWH_{t-1}/ CSTM_{t-1})} - \underset{(+)}{b_4\alpha_1 LnYCAP_{t-1}} - \underset{(-)}{b_4\alpha_2 LnP_{t-1}} - \underset{(+)}{b_4\alpha_3 LnHDD_{t-1}} + v_t \qquad (5)$$

Equation 5 can be re-written more succinctly.

$$dLn(KWH_t/CSTM_t) = g_0 + \underset{(+)}{g_1}dLnYCAP_t + \underset{(-)}{g_2}dLnP_t + \underset{(+)}{g_3}dLnHDD_t + \underset{(-)}{g_4}Ln(KWH_{t-1}/CSTM_{t-1}) +$$

$$\underset{(+)}{g_5}LnYCAP_{t-1} + \underset{(-)}{g_6}LnP_{t-1} + \underset{(+)}{g_7}LnHDD_{t-1} + v_t$$

Determining the increase in customers is an important step in planning for the expansion of service, as new meters and distribution lines must be installed for new residences. Accordingly, an equation is also specified for the number of customers. Fullerton, et al (2007) estimate residential water customers for Tijuana using monthly maquiladora employment and the industrial production index for Mexico. These data are used in place of population because monthly population data do not exist for Tijuana. Because such data do exist for this market, population is used to model new customer growth (Equation 6).

$$LnCSTMt = \theta_0 + \underset{(+)}{\theta_1}LnPOPt \tag{6}$$

IV. Estimation Results

This section examines the estimation results of the model. Because the main focus of the paper is electricity consumption per customer, the long-run equation estimates per capita consumption and is expressed in Equation 1. The price variable (PCPI) has an endogenous relationship with the dependent variable kilowatt-hour per customer (KWHC). Kilowatt-hours per customer is a function of price, real per capita income, and heating degree days, but according to traditional economic theory, price is a function of demand. This bi-directional relationship could generate a contemporaneous correlation between the endogenous independent price variable and the error-term (Pindyck and Rubinfeld, 1998).

$$LnKWHC_t = \alpha_0 + \underset{(+)}{\alpha_1 LnYCAPt} + \underset{(-)}{\alpha_2 LnP_t} + \underset{(+)}{\alpha_3 LnHDD_t} + u_t \qquad (1)$$

To test if the error-term is correlated with the price variable, the demand equation is estimated utilizing instrumental variables. Proper selection of instrumental variables satisfies two conditions: 1) it is correlated with the endogenous independent variable, real price per kilowatt-hour and, 2) the instrumental variables are not correlated with the error-term (Pindyck and Rubinfeld, 1998). National fixed asset prices, structures (STRUC) are used as an instrumental variable because SCL's revenues are based upon operating and capital costs of the federal electric power system, mainly dams and transmission facilities (Lee, et al, 1980). These costs are transferred to electricity prices charged to customers.

The second instrument is the national electricity price index (ELECP). National electricity prices affect the rate SCL is charged for off-system power purchases, and the rate SCL charges other electricity utility companies. Both of these variables are obtained from the Bureau of Economic Analysis National Income and Product Accounts Tables.

$$LnKWHC_t = \alpha_0 + \alpha_1 LnYCAPC_t + \alpha_2 LnPCPI_t + \alpha_3 LnHDD_t + \alpha_4 LnSTRUC_t + \alpha_5 LnELECP_t + u_t \quad (2)$$

The residuals (RESID01) generated from the estimation will be put into the original specification outlined in Equation 1. This will test if the error-term is correlated with PCPI. The null hypothesis, H_0, is that PCPI is not correlated with the error-term. The residuals are used as an estimate of the error-term. If the t-statistic of the residuals is greater than 2 standard deviations, H_0 is rejected. According to the results reported in Table 1, H_0 is rejected and PCPI is correlated with the error-term.

Table 1 Artificial Regression Equation
Dependent Variable: LOG(KWHC)
Method: Least Squares
Sample (adjusted): 1969 2007
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.2082	0.9504	11.7921	0.0000
LOG(YCAPC)	-0.4020	0.0421	-9.5278	0.0000
LOG(PCPI)	-0.2231	0.0384	-5.8080	0.0000
LOG(HDD)	0.2655	0.0886	2.9950	0.0051
RESID01	1.0000	0.2110	4.7380	0.0000

R-squared	0.9333	Mean dependent var	9.324829
Adjusted R-squared	0.9255	S.D. dependent var	0.127820
S.E. of regression	0.0348	Akaike info criterion	-3.754458
Sum squared resid	0.0413	Schwarz criterion	-3.541181
Log likelihood	78.2119	Hannan-Quinn criter.	-3.677936
F-statistic	119.0588	Durbin-Watson stat	0.204513
Prob(F-statistic)	0.0000		

A price equation is estimated to generate fitted price values (PCPIHAT), and the demand equation is re-estimated, (Nieswiadomy and Molina, 1989). The regression equation utilizes the instruments and the exogenous variables, real per capita income (YCAPC) and heating degree days (HDD). The specification is expressed in Equation 3.

$$LnPCPI = C_0 + C_1 LnYCAPC_t + C_2 LnHDD_t + C_3 LnSTRUCt + C_4 LnELECP_t + v_t \quad (3)$$

As mentioned earlier, instrumental variables must satisfy two primary conditions. According to SCL's annual reports, it is the 9th largest public utility in the United States. Given the number of investor-owned electricity utility companies operating in the United States, in addition to the number of publicly owned utilities operating domestically, SCL's impact on the national indexes are little to none. This demonstrates a unidirectional relationship, and not an endogenous relationship satisfying condition number two of the instrumental variable selection criteria.

The Seattle CPI has a 1982-1984 CPI average base value of 1. Results of the price estimation are reported in Equation 4 with their respective t-stats in brackets. A second residual series is generated (RESIDLR), and the fitted values are equal to PCPI-RESIDLR in actual application. The demand equation with the new fitted values is expressed in Equation 5 with corresponding results reported in Table 2.

$$\underset{}{LnPCPIHAT_t} = -13.0295 + \underset{[-2.0656]}{1.1670}*LnYCAPC_t + \underset{[-0.7439]}{0.3522}*LnHDD_t - \underset{[0.6111]}{0.3199}*LnSTRUC_t + \underset{[2.0448]}{0.1921}*LnELECP_t + u_t \quad (4)$$

$$\text{[0.8912]}$$

$$LnKWHC_t = \alpha_0 + \alpha_1 LnYCAPC_t + \alpha_2 LnPCPIHAT_t + \alpha_3 LnHDD_t + u_t \quad (5)$$

Table 2 Long-Run Demand Equation
Dependent Variable: LOG(KWHC)
Method: Least Squares
Sample (adjusted): 1969 2007
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.9760	1.4079	7.0852	0.0000
LOG(YCAPC)	-0.2947	0.0780	-3.7770	0.0006
LOG(PCPIHAT)	-0.3656	0.0884	-4.1327	0.0002
LOG(HDD)	0.3030	0.1185	2.5565	0.0151

R-squared	0.8812	Mean dependent var	9.3248
Adjusted R-squared	0.8710	S.D. dependent var	0.1278
S.E. of regression	0.0459	Akaike info criterion	-3.2276

Sum squared resid	0.0737	Schwarz criterion	-3.0570
Log likelihood	66.9398	Hannan-Quinn criter.	-3.1664
F-statistic	86.5514	Durbin-Watson stat	0.4389
Prob(F-statistic)	0.0000		

The regression results indicate that the explanatory variables are all significant at the 95 percent level. Real average price and heating degree days have their expected signs. An increase in real price lead to reduced electricity use. The magnitude of the price elasticity is somewhat lower than other research findings, in absolute terms. Halicioglu (2007) reports the long-run price elasticity at -0.63. Zachariadis and Pashourtidou (2007) obtain a -0.43 price elasticity for residential electricity demand. Similar results are reported by Narayan, et al (2007) for France and Canada at -0.30 and -0.50, respectively. Nieswiadomy and Molina (1989) report price elasticities of -0.09 and -0.86 using the instrumental variables estimation method for their Dallas metropolitan water demand study.

Table 2 also indicates that decreases in temperature lead residents to increase their electricity consumption. A 1 percent increase in heating degree days will increase residential electricity use by 0.303 percent. This magnitude is smaller than the own-price elasticity coefficient. Other studies have supported these findings (Dergiades and Tsoulfidis, 2007), while Maddigan, et al's (1983) study find that rural customers in the northwest region responded more to fluctuations in temperature than to changes in price.

What is somewhat surprising is the negative sign for real per capita income. Increases in per capita income generate a long-run reduction of home electricity use by 0.294 percent. Income elasticity is expected to be positive for any normal or superior good. In Seattle, electricity may be an inferior good, similar to what is reported in Roth (1981) and Contreras, et al (2009). The income-elasticity magnitude is fairly close to that estimated by Contreras, et al (2009) using national data.

Short-run dynamics must be utilized to evaluate immediate customer response to rising electricity costs. To confirm if there is a long-run relationship, an Augmented Dickey-Fuller (ADF) test is performed. This test will determine the order of cointegration, if such a relationship exists. The null hypothesis (H_0) is that the residuals from the long-run equation do contain a unit-root. Existence of a unit-root indicates that a cointegration relationship does not exist (Kennedy, 2003). Table 3 reports the ADF test statistic for the level residual data. Unit roots are rejected for the residuals.

Table 3 KWH Unit-Root Test
Null Hypothesis: RESIDLR has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.0361	0.0414
Test critical values:	1% level	-2.6272	
	5% level	-1.9498	
	10% level	-1.6114	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDLR)
Method: Least Squares
Sample (adjusted): 1970 2007
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDLR(-1)	-0.2152	0.1057	-2.0361	0.0489

R-squared	0.1004	Mean dependent var	-0.0005
Adjusted R-squared	0.1004	S.D. dependent var	0.0295
S.E. of regression	0.0280	Akaike info criterion	-4.2837
Sum squared resid	0.0291	Schwarz criterion	-4.2406
Log likelihood	82.3909	Hannan-Quinn criter.	-4.2683
Durbin-Watson stat	2.0589		

The residual series generated from the long-run estimation is used as a proxy for the error-correction term, u_{t-1}. This data series are used in the short-run estimate of the error-correction parameter, b_4. The short-run equation is specified in Equation 6. The results of the short-run equation are found in Table 4.

$$dLnKWHC_t = b_0 + b_1 dLnYCAPC_t + b_2 dLnPCPIHAT_t + b_3 dLnHDD_t + b_4 u_{t-1} + w_t \quad (6)$$

Table 4 Short-Run Demand Equation
Dependent Variable: DLOG(KWHC)
Method: Least Squares
Sample (adjusted): 1970 2007
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.0106	0.0043	-2.4366	0.0204
DLOG(YCAPC)	0.2614	0.1291	2.0250	0.0510
DLOG(PCPIHAT)	-0.2442	0.0803	-3.0377	0.0046
DLOG(HDD)	0.3388	0.0464	7.2964	0.0000
RESIDLR(-1)	-0.1923	0.0881	-2.1805	0.0365

R-squared	0.6732	Mean dependent var	-0.0082
Adjusted R-squared	0.6336	S.D. dependent var	0.0380
S.E. of regression	0.0230	Akaike info criterion	-4.5807
Sum squared resid	0.0175	Schwarz criterion	-4.3653
Log likelihood	92.0347	Hannan-Quinn criter.	-4.5041
F-statistic	16.9987	Durbin-Watson stat	2.4214
Prob(F-statistic)	0.0000		

According to Dergiades and Tsoulfidis (2008), all short-run coefficients should be less than their long-run counter parts in absolute terms. Own-price elasticity keeps its negative sign and changes the magnitude as expected. However HDD has a higher short-run elasticity than in the long-run. This could be due to the high number of electric heating systems found in the Seattle area. The income variable changes signs indicating that customers are willing to increase end-use consumption of the incumbent stock of electricity-using equipment as real-income rises. The long-run estimation reflects replacement of the incumbent capital stock, demonstrating that increases in long-run income lead to more energy efficient capital stocks (Contreras, 2009).

According to the model, the error-correction parameter represents the deviation from equilibrium levels. When the error-correction term is rewritten in terms of the lagged explanatory variables, their parameters will adjust by b_4, as shown in Equation 7. Multiplying b_4 throughout the parenthetic terms, combining like terms, and simplifying, we obtain Equation 8. Table 5 shows the estimated coefficients for the short-run equation, long-run equation, and error-corrected adjusted parameters. The equilibrium long-run electricity consumption is achieved if the explanatory variable coefficients adjust by an amount equal to long-run parameters times the error-corrected adjustment.

$$dLnKWHC_t = b_0 + b_1 dLnYCAPC_t + b_2 dLnP_t + b_3 dLnHDD_t + b_4(LnKWHC_{t-1} - \alpha_0 - \alpha_1 LnYCAP_{t-1} - \alpha_2 LnP_{t-1} - \alpha_3 LnHDD_{t-1}) + v_t \quad (7)$$

$$dLnKWHC_t = g_0 + \underset{(+)}{g_1 dLnYCAP_t} + \underset{(-)}{g_2 dLnP_t} + \underset{(+)}{g_3 dLnHDD_t} + \underset{(-)}{g_4 LnKWHC_{t-1}} + \underset{(+)}{g_5 LnYCAP_{t-1}} + \underset{(-)}{g_6 LnP_{t-1}} + \underset{(+)}{g_7 LnHDD_{t-1}} + v_t \quad (8)$$

Table 5 Long-run, Short-run, Error-Corrected Adjustments

Long-Run Parameters	Short-Run Parameters	Error-Correction Adjustment, b4
a_0=9.976	b_0 = -0.0106	$b_4a_0 = g_5$ =-1.9183
a_1= -0.2947	b_1 = 0.2614	$b_4a_1 = g_6$ = 0.0566
a_2= -0.3656	b_2 = -0.2442	$b_4a_2 = g_7$ = 0.0703
a_3= 0.3030	b_3 = 0.3388	$b_4a_3 = g_8$ = -0.0582
-----	b_4 = -0.1923	-----

Below are the long-run (9), and short-run (10) equation estimations. The error-correction adjustments for the long-run variables are shown in Equation 11. The error-correction parameter is used to calculate the residual dissipation rate. The residual dissipation rate is 5.18 years, or $1/b_4$. This rate reflects how long it takes customers to adjust their electricity consumption to an equilibrium level following any deviation from it during the prior period.

$$LnKWHC_t = 9.9760 – 0.2947*LnYCAPC_t – 0.3656*LnPCPIHAT_t + 0.3032*LnHDD_t$$

$+ u_t$ (9)

$dLnKWHC_t = -0.0106 + 0.2614*dLnYCAPC_t – 0.2442*dLnPCPIHAT_t + 0.3388dLnHDD_t$

$– 0.1923*u_{t-1} + v_t$ (10)

$b4u_{t-1} = -0.1923*LnKWHC_t + 0.0566*LnYCAPC_t + 0.0703*LnPCPIHAT_t – 0.0582*LnHDD_t$

$+ v_t$ (11)

To test the stability of the long-run coefficients, a cumulative sum (CUSUM) and CUSUM of squares test (CUSUMQ) are carried out on the residuals of the error-correction model specified in Equation 6. A CUSUM stability test measures the systematic movements of the coefficients. The null hypothesis is the coefficients are stable. H_0 is rejected if the cumulative sum exceeds the specified critical boundaries, demonstrating instability among the coefficients (Maddala and Kim, 1998). A CUSUMQ test measures stability of the variance. Both tests reveal coefficient and variance stability as the residuals and squared residuals move within the 5-percent critical boundaries, failing to reject the null hypothesis.

Figure 1 CUSUM Test KWH

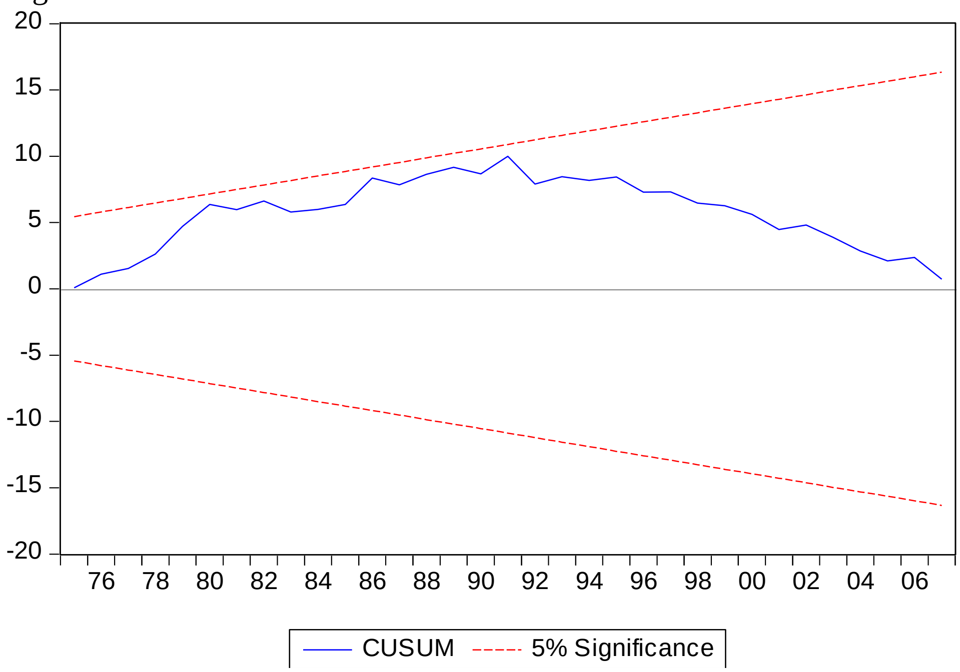
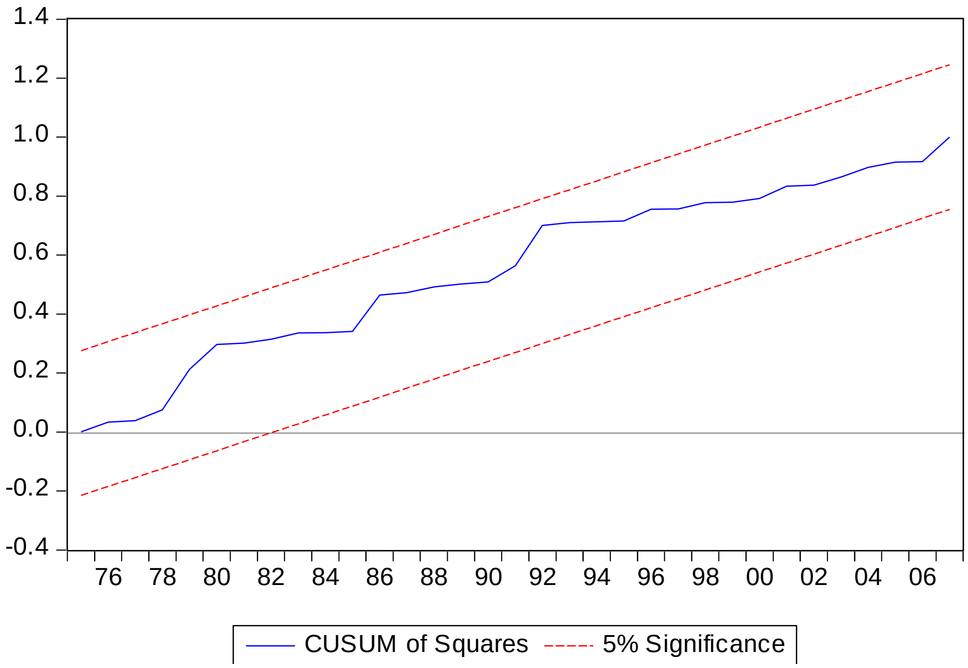


Figure 2 CUSUMSQ Test KWH



It is important for utility companies to anticipate service growth. Such anticipation allows for informed decision into how much new investment is needed to expand capacity. Accordingly, it is useful to also understand how the customer base varies. Population and employment are used as the explanatory variables to account for both economic and demographic conditions, and subsequent migratory responses to these conditions (Fullerton, et al, 2007). This is best represented by a current population variable (POP_t) and a lagged employment variable (EMP_{t-1}). See Equation 12.

$$LnCSTM_t = \theta_0 + \underset{(+)}{\theta_1 LnPOP_t} + \underset{(+)}{\theta_2 LnEMP_{t-1}} + p_t \tag{12}$$

Equation 12 yields very good results for the customer equation. R^2 is reported at 0.970, while t, F, and X^2 statistics satisfy the 95-percent confidence interval. Results show that a 1-percent increase in economic conditions, as measured by employment increases customer growth by nearly 0.50 percent. Results also indicate that population growth has an equal impact on new customer growth at the 5-percent significance level. The Durbin-Watson statistic suggests the presence of serial correlation. Estimation of the autocorrelation function (ACF) also indicates the presence of serial correlation. Unfortunately, various autoregressive moving average (ARMA) specifications fail to satisfy the two standard deviation threshold of the ACF, fail to satisfy the 95-percent confidence interval, and/or have parameters near 1. Lack of satisfactory results led to the long-run specification reported in Table 6.

Table 6 Long-Run Customer Equation
Dependent Variable: LOG(CSTM)
Method: Least Squares
Sample (adjusted): 1971 2007
Included observations: 37 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.7348	0.5841	11.5291	0.0000
LOG(POP)	0.4601	0.1086	4.2362	0.0002
LOG(EMP(-1))	0.4628	0.0275	16.8152	0.0000
R-squared	0.9706	Mean dependent var		12.5485
Adjusted R-squared	0.9688	S.D. dependent var		0.1255
S.E. of regression	0.0221	Akaike info criterion		-4.7056
Sum squared resid	0.0166	Schwarz criterion		-4.5750
Log likelihood	90.0552	Hannan-Quinn criter.		-4.6596
F-statistic	561.7165	Durbin-Watson stat		0.3853
Prob(F-statistic)	0.0000			

The need for short-run estimation for electricity consumption is much more apparent than the need for short-run estimation of new customers. Short-run end-use consumption can be explained by lowering a thermostat, turning off light-bulbs, and can go as far as unplugging appliances when idle. What does the "short-run" model for new customers represent?

Understanding short-run characteristics of new customer growth requires some deconstructive work on the general assumptions about population and employment. It is unrealistic to think that all the new arrivals to the SCL market are unemployed. Some of these individuals have the income or savings needed to establish a new residency upon arrival. Further, some new arrival income-earners have children or spouses whom do not earn any form of income, while some existing customers and their families may move out of their current homes. That reflects a gain of *n* customers and a loss of *m* customers, or more succinctly, the number of existing electricity-meters that are turned on or off.

To confirm if there is a long-run relationship, an Augmented Dickey-Fuller (ADF) test is performed on the residuals (RESIDCS) from the long-run customer equation. H_0 is still the same as the ADF performed on the residuals from the demand model (See Table 3). If H_0 is rejected, then the residuals do not contain a unit root, and a cointegrating relationship exists. The deviation from long-run equilibrium is expressed via the adjustment, or error-correction parameter. Table 7 reports rejection of H_0, and stationarity is achieved with first differencing.

Table 7 CSTM Unit-Root Test
Null Hypothesis: RESIDCS has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.0782	0.0031
Test critical values:	1% level	-2.6326	
	5% level	-1.9506	
	10% level	-1.6110	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDCS)
Method: Least Squares
Sample (adjusted): 1973 2007
Included observations: 35 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDCS(-1)	-0.2906	0.0944	-3.0782	0.0042
D(RESIDCS(-1))	0.5366	0.1425	3.7658	0.0007

R-squared	0.3453	Mean dependent var	0.0011
Adjusted R-squared	0.3255	S.D. dependent var	0.0130
S.E. of regression	0.0107	Akaike info criterion	-6.1795
Sum squared resid	0.0037	Schwarz criterion	-6.0907
Log likelihood	110.1427	Hannan-Quinn criter.	-6.1489

Durbin-Watson stat	2.0350

Before estimating the short-run customer equation, the residuals are used as a proxy for the error-correction term p_{t-1}. This data series is used in the short-run estimate of the error-correction parameter, λ_3. The short-run equation is expressed in Equation 13, with subsequent results reported in Table 8.

$$dLnCSTM = \lambda_0 + \underset{(+)}{\lambda_1 dLnPOP_t} + \underset{(+)}{\lambda_2 dLnEMPt_{-1}} + \underset{(+)}{\lambda_3 p_{t-1}} + q_t \tag{13}$$

Table 8 Short-Run Customer Equation
Dependent Variable: DLOG(CSTM)
Method: Least Squares
Sample (adjusted): 1972 2007
Included observations: 36 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0091	0.0014	6.3074	0.0000
DLOG(POP)	0.1000	0.1757	0.5693	0.5731
DLOG(EMP(-1))	0.0974	0.0427	2.2815	0.0293
RESIDCS	0.0564	0.0592	0.9530	0.3477

R-squared	0.1583	Mean dependent var	0.0112
Adjusted R-squared	0.0794	S.D. dependent var	0.0073
S.E. of regression	0.0070	Akaike info criterion	-6.9686
Sum squared resid	0.0015	Schwarz criterion	-6.7926
Log likelihood	129.4352	Hannan-Quinn criter.	-6.9072
F-statistic	2.0069	Durbin-Watson stat	2.1264
Prob(F-statistic)	0.1327		

The results support Dergiades and Tsoulfidis (2008) contention that short-run coefficients are less than the long-run parameters. Significance is lost at the 5 percent level for population. This is to be expected, because population includes non-income earners such as children and unemployed non-retirees, as well as income earners themselves. Customers are attached to the individuals who have income or savings, and are better represented by the employment variable.

Lagged employment continues to satisfy the 5 percent significance level. The low coefficient estimate for the error-correction term, along with the insignificant t-statistic demonstrates that the short-run customer equation does not contain significant error. To test for consistency of the long-run multipliers, a CUSUM and CSUMSQ tests are run (Pesaran and Pesaran, 1997). Both CUSUM and CUSUMSQ tests demonstrate coefficient stability.

Figure 3 CUSUM CSTM

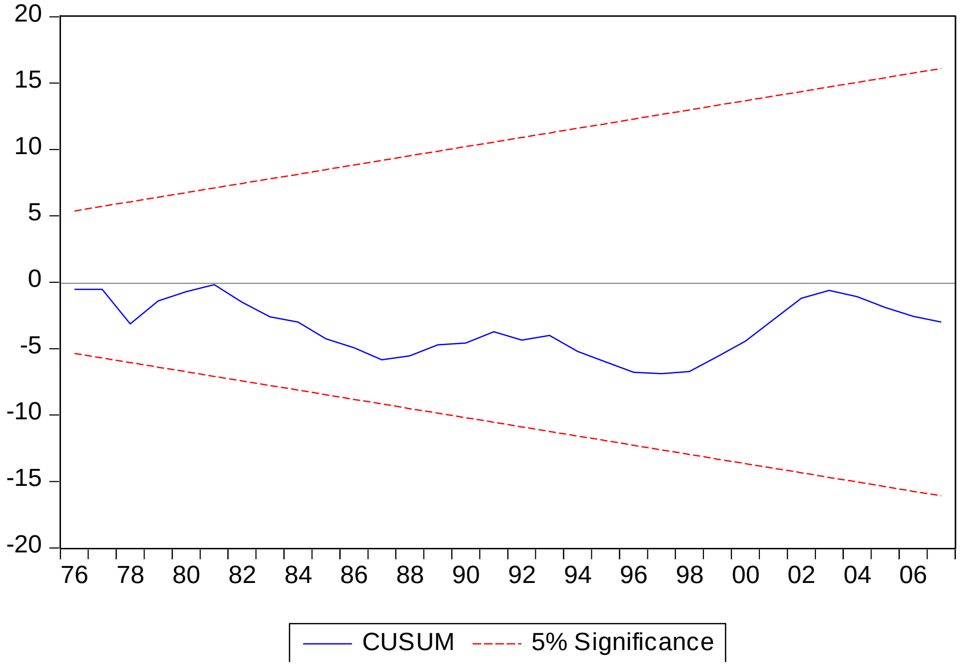
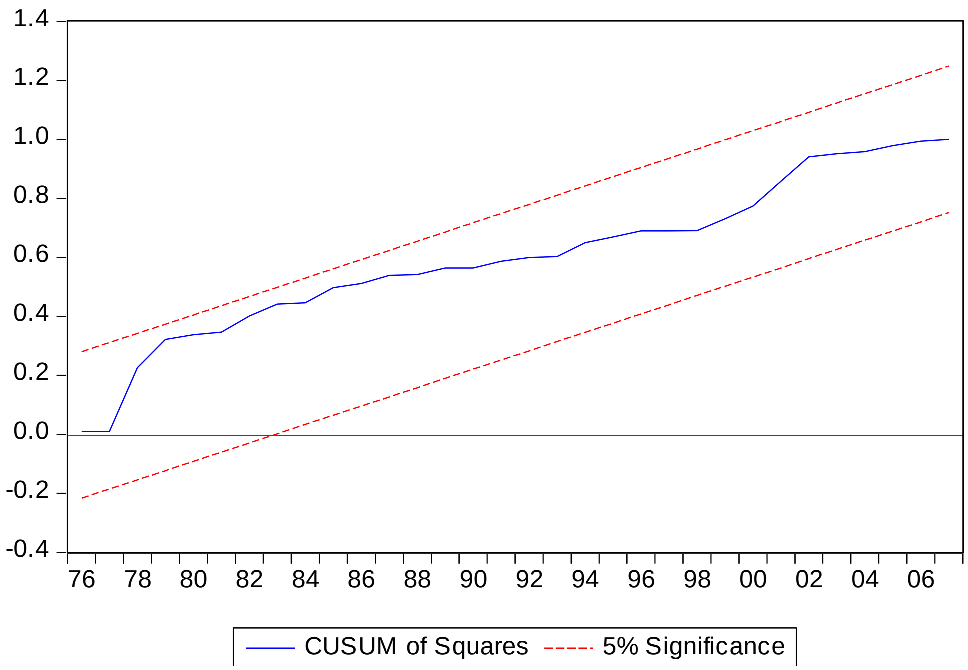


Figure 4 CUSUMSQ Test CSTM



A 3-period out-of-sample forecast is simulated for KWHC and CSTM. The forecast period will use the compound annual growth rates (CAGRs) from 2004-2007 for the explanatory variables. The CAGR sample period is selected because it reflects the most recent trend in the data, capturing current influences and behaviors of Seattle residents (Lakhani and Bumb, 1978). HDD is the only variable in which the growth rate is assumed fixed, and the historical value of 4,837 is used. It should be noted that the historical sample occurred before the financial collapse of 2008.

Real per capita income has a CAGR of 1.375 percent. CAGR for the fitted price variable, PCPIHAT has a CAGR of -2.339 percent. The fitted values maintain some consistency with actual observed values. Nominal price decreased by 0.842 percent from 2004 to 2007. However when the CAGR for the Seattle CPI is calculated over the same period, a 2.588 percentage increase occurred causing a real price decrease of 3.253 percent [(0.842/2.588)*100]. Population increased less than 1-percent over the same period, with a CAGR of 0.413 percent. Employment rose 1.7854 percent exceeding the population growth experienced over that same 3 year period. Table 9 reports the estimated CAGRs for the explanatory variables.

Table 9 CAGR Estimates

	Explanatory Variables				
	YCAPC	PCPIHAT	HDD	POP	EMP
CAGR(%)	*1.357*	*-2.339*	-----	*0.413*	*1.785*
2008	24,942	2.9503	4,837	749.2816	592.7980
2009	25,286	2.8813	4,837	752.3758	603.3817
2010	25,633	2.8139	4,837	755.482	614.1544

Table 10 reports the forecasts for the dependent variables and their respective percentage changes between the forecast periods. Forecasts for kilowatt-hours per customer range between

9,579 and 9,668 for the 3-year period, and consist of percentage increases of just under 0.50 percent. These percentage changes indicate a real income effect that is partially offsetting the impact of real price. According to the model reported in Table 2, the decline in price should increase end-use consumption at a rate of 0.86 percent (α_2 x -2.339) per annum. The real-income coefficient has reduced this rate by half. This offsetting income percentage may reflect the replacement of the incumbent electricity-using stock with more energy efficient ones.

The customer forecasts report annual growth rates of just over 1.01 percent. The rate of increase of employed residents exceeds the increase in total population. This could mean a variety of things including, an increase of the current population is reaching employment age. It could also reflect economic growth. As the demand for labor rises more members of the Seattle labor pool are finding employment.

If the impact of in-bound migration to Seattle is considered, the role of employment is even greater. As this rise of the employed population increases at this rate, forecasts show that SCL should be prepared to supply electricity to a steadily growing number of customers. A potential X-factor is residents who reside outside the service area who simply work in the SCL service market, and are not part of the residential electricity demand market. Total kilowatt-hour consumption is equal to CSTM x KWHC. These results and percentage changes are also reported in Table 10.

Table 10 Forecasts

	Forecasts					
YEAR	KWHC	%ΔKWHC	KWH (‘000S)	%ΔKWH	CSTM	%ΔCSTM
2008	9,579	----	3,227,634	----	336,949	----
2009	9,623	0.4600	3,275,332	1.4778	340,365	1.0138
2010	9,668	0.4700	3,324,013	1.4863	343,816	1.0139

V. Conclusion

This study analyzes residential electricity demand in Seattle. An error-correction model is estimated for this market. An artificial regression technique is also employed due to simultaneity between the consumption and price variables. Fitted price values are estimated and used in both the long-run and short-run models.

Residents of the Seattle City Light Service market have an inelastic response to price change. Long-run and short-run price elasticities are inelastic with estimates equal to -0.3656 and -0.2442, respectively. Long-run real income results report an elasticity of -0.2947, indicating that electricity is an inferior good in Seattle. That outcome is similar to what has been documented for other regional markets and for the United States as a whole. Short-run estimates report that customers are willing to increase end-use consumption as their disposable income levels rise, indicating electricity is a normal good in the short-run.

Forecasts for kilowatt-hours per customer are also generated. Recent historical compound annual growth rates of the explanatory variables are used for the out-of-sample simulations. Prices decreased over the 2004-2007 sample period. The price-effect is reduced by the real income elasticity, and resulted in per customer consumption increases of just under 0.50 percent.

Planning for new customers is a major concern for utility companies. Determining the increase in the number of customers is important in planning for the expansion of service, as new meters and distribution lines must be installed for new residencies. New customers is estimated as a function of population and lagged employment. An error-correction model is estimated for the customer equation. Long-run results report nearly identical elasticity estimates for population and employment with coefficients equal to 0.4601and 0.4628. The short-run model attributes new customers to employment rather than population, potentially reflecting the impacts of migration on the electricity grid.

Customer forecasts show a 1.01 percent increase per annum between 2008 and 2010. The increase as the model indicates is generally driven by increases in employment. Employment increase percentages exceeded those of population by 1.03 percent. Proper planning for such a steady increase will determine how well SCL can handle the increased costs needed to power these new customers.

The results of the study are interesting, specifically the income estimate. It will be interesting to see if monthly and quarterly data will replicate similar results. Other metropolitan electricity demand studies need to be conducted to determine how income impacts electricity demand in their specific regions.

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Appendix

Table A1: Historical data for Seattle City Light Data Series

Year	Total Residential Elecricity Consumption	Residential Electricity Consumption per Customer	Total Revenue	Average Revenue per kilowatt-hour	Number of customers
1960	1,902,276,324	9,133	18,356,967	0.96500	208,294
1961	1,950,084,410	9,281	18,759,812	0.96200	210,112
1962	2,084,739,626	9,669	19,867,569	0.95300	215,612
1963	2,130,183,006	9,902	20,258,040	0.95100	215,123
1964	2,198,195,167	10,288	20,728,980	0.94300	213,671
1965	2,245,623,253	10,303	20,547,453	0.91500	217,962
1966	2,359,760,284	10,494	21,308,635	0.90300	224,860
1967	2,481,720,687	10,947	21,814,325	0.87900	226,713
1968	2,665,715,427	11,555	23,165,067	0.86900	230,706
1969	2,859,783,286	12,346	24,679,930	0.86300	231,628
1970	2,860,659,583	12,340	24,601,672	0.86000	231,817
1971	2,988,865,136	13,042	26,182,459	0.87600	229,179
1972	3,016,438,527	13,203	27,721,070	0.91900	228,472
1973	2,947,345,300	12,689	27,203,997	0.92300	232,280
1974	2,891,138,710	12,370	26,916,501	0.93100	233,720
1975	3,014,971,273	12,813	30,601,958	1.01500	235,314
1976	3,118,048,041	13,060	31,554,646	1.01200	238,755
1977	3,067,111,885	12,410	38,522,925	1.25600	247,148
1978	3,068,327,988	12,415	36,298,320	1.18300	247,142
1979	3,227,585,671	12,782	37,988,683	1.17700	252,505
1980	3,346,362,000	13,089	44,841,251	1.34000	255,665
1981	3,263,530,000	12,543	52,216,480	1.60000	260,180
1982	3,365,994,000	12,894	66,310,082	1.97000	261,060
1983	3,099,908,000	11,829	75,327,764	2.43000	262,061
1984	3,223,790,000	12,119	86,397,572	2.68000	266,010
1985	3,329,146,000	12,376	100,207,295	3.01000	268,995
1986	3,233,897,000	11,884	100,250,807	3.10000	272,131
1987	3,068,650,000	11,184	99,424,260	3.24000	274,383
1988	3,218,714,000	11,548	107,505,048	3.34000	278,724
1989	3,271,220,000	11,479	110,894,358	3.39000	284,984
1990	3,261,285,000	11,250	109,579,176	3.36000	289,888
1991	3,349,065,000	11,321	112,193,678	3.35000	295,816
1992	3,068,067,000	10,313	105,848,312	3.45000	297,496
1993	3,260,890,000	10,810	121,305,108	3.72000	301,647

1994	3,157,205,000	10,465	119,342,349	3.78000	301,679
1995	3,109,816,000	10,257	121,904,787	3.92000	303,199
1996	3,267,794,000	10,739	132,345,657	4.05000	304,287
1997	3,221,824,000	10,507	136,927,520	4.25000	306,629
1998	3,189,109,000	10,335	136,174,954	4.27000	308,564
1999	3,322,835,000	10,621	142,881,905	4.30000	312,849
2000	3,267,710,000	10,316	150,641,431	4.61000	316,758
2001	3,050,900,000	9,454	187,935,440	6.16000	322,707
2002	3,045,768,000	9,311	210,157,992	6.90000	327,127
2003	2,952,615,000	8,921	199,301,513	6.75000	330,979
2004	2,952,664,000	8,852	199,304,820	6.75000	333,560
2005	2,954,848,000	8,785	195,610,938	6.62000	336,364
2006	3,060,651,000	9,011	201,390,836	6.58000	339,640
2007	3,103,550,000	9,034	196,144,360	6.32000	343,542

Table A2: Historical data for Seattle Economic, Population and Climate Data Series

Year	Per capita personal income	Seattle Urban Consumer Price Index	Seattle Employment	Population	Heating Degree Days
1970	4856	0.374	302.00	683.30	4958.5
1971	4980	0.381	289.61	674.70	5437
1972	5373	0.393	297.26	663.10	5270
1973	5974	0.418	308.06	660.10	5001
1974	6654	0.464	315.88	652.60	4768
1975	7476	0.511	318.19	648.70	5185
1976	8276	0.539	324.06	646.70	4695
1977	9136	0.582	340.30	643.80	4616.5
1978	10485	0.640	371.34	640.90	4726
1979	11872	0.709	396.58	638.00	4520
1980	13152	0.827	406.48	635.10	5049.5
1981	14550	0.916	404.75	634.80	4693
1982	15423	0.978	396.07	634.90	5124
1983	16094	0.993	389.70	636.00	4577
1984	17351	1.030	404.33	638.60	5060
1985	18471	1.055	408.97	641.90	5687
1986	19530	1.066	422.47	645.30	4615
1987	20530	1.092	432.06	649.70	4343.5
1988	22021	1.129	447.24	654.90	4786.5
1989	23773	1.182	472.95	661.90	4711
1990	25452	1.268	489.72	667.70	4857.5
1991	26543	1.341	491.16	675.30	4636
1992	27904	1.390	495.04	684.90	4169.5
1993	28228	1.429	489.06	691.70	4771.5
1994	29370	1.478	493.08	694.80	4414
1995	30626	1.522	499.52	699.50	4063.5
1996	32592	1.575	513.81	705.40	5023
1997	34250	1.630	531.62	713.00	4682.5
1998	38236	1.678	560.43	719.30	4579
1999	42217	1.728	579.08	723.30	5038
2000	44437	1.792	597.12	724.85	5049
2001	43843	1.858	571.39	731.15	5064.5
2002	44313	1.894	550.50	732.08	5020
2003	44483	1.925	538.45	732.74	4604
2004	49273	1.947	542.58	733.99	4495
2005	48072	2.001	553.58	737.22	4567
2006	51925	2.079	569.93	741.62	4558
2007	52840	2.1566	582.40	746.20	4903

Notes: 1. Total residential electricity consumption values are reported in kilowatt-hours.
2. Residential electricity consumption per customer values are reported in kilowatt-hours.

3. Total revenue values are reported in nominal dollars.
4. Customer values represent one residential meter billed.
5. Average revenue per kilowatt-hour values are reported in nominal cents.
6. Per capita income data are reported in nominal dollar values.
7. Seattle consumer price index has a 1982-1984 average base value of 1.
8. Employment values are reported in thousands.
9. Population values are reported in thousands.
10. Heating degree day units are equal to the base temperature less the daily average temperature.

Curriculum Vita

David Juarez was born in Los Angeles, California, on September 11, 1982. His parents are Francisco Juarez, Jr. and Dawn Marie Heslip. He and his father moved to El Paso sometime in 1988, where he and his father were homeless for many years. He graduated from Ysleta High School in 2000, and had previously attended Riverside High School between 1996 and 1998. He received his Bachelor of Arts in Economics from the University of Texas at El Paso in December of 2007. Having an arts degree allowed him to have a different perspective than those that had attended the business college. As a graduate student he worked as a teaching assistant for the Department of Economics and Finance and the Department of Information and Decision Sciences at UTEP. After a few years of working, he plans to continue his education by pursuing a Juris-Doctorate in Economic or International Comparative Law.