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El Paso Residential Electricity Demand

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EL PASO RESIDENTIAL ELECTRICITY DEMAND

by

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Abstract

This study utilizes a dynamic error correction model to analyze the demand for residential electricity in El Paso County, Texas. Annual data is provided by El Paso Electric Company covering the period from 1977 to 2011. This study reports negative income elasticities for residential electricity demand and indicates that electricity is treated as an inferior good in El Paso County. The negative income elasticity result runs counter to many earlier studies, although recent empirical evidence indicates that residential electricity is also treated as an inferior good in the Seattle service territory. Negative income elasticities are an interesting result, and may allow electric utilities to utilize existing generating capacity to sufficiently provide power to the service territory, even if the economy continues to expand. Further examination of electricity consumption behavior at the regional level is warranted. This study reports that in the long run, per capita residential electricity usage declines by 0.36 percent for every 1 percent increase in real per capita income.

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Chapter 1: Introduction

Most of the existing empirical evidence for the demand of electricity indicates a positive relationship between income and consumption. Positive income elasticities in a demand model are indicative of a normal good. While there are many studies that indicate electricity is a normal good (Dergiades and Tsoulfidis, 2008), there also exists some studies that indicate electricity is an "inferior good" with sales that are negatively correlated with incomes (Roth, 1981). Recent empirical evidence indicates that residential electricity is an inferior good in the United States (Contreras et al., 2009).

Correctly forecasting the demand for electricity consumption is crucial for electric utilities throughout the United States. The construction of a new generating unit to serve increases in native load demand can take several years to complete. Electric utilities have very small windows for error in determining when to file for a new permit to construct new generating plant additions. Knowledge of the demand for electricity and the accurate estimation of future demand growth have important economic and regulatory repercussions and is a critical element in the planning process for all utility companies (Dortolina and Nadira, 2005).

Classical demand theory systematically includes income as a determinant (Barten, 1968). Recent evidence of a negative income elasticity at the national level calls for similar research at the local level. Most utilities do not serve native loads that encompass entire states and, therefore, are more interested in localized service regions. There is also the possibility for income heterogeneity among different regions of the same state. Income heterogeneity may lead to biased estimators, especially in large states such as Texas where income disparity is quite large (Wooldridge, 2009).

This study attempts to model residential electricity consumption in El Paso County, Texas. Electricity demand for the County of El Paso is served by El Paso Electric Company. El Paso Electric Company is an investor-owned utility providing electric energy to approximately 380,000 retail customers in a 10,000 square mile area of the Rio Grande Valley in west Texas and southern New Mexico. The Company has a net dependable generating capability of approximately 1,785 MW's, and a 2011 native peak demand of 1,711 MW's. New generation is already under construction to keep pace with an estimated compound annual growth rate in megawatt peak demand of 2.90 percent over the 2011 to 2020 period (Patton, 2012). An application to construct additional generation filed with the Public Utility Commission of Texas by El Paso Electric in May of 2012 also includes a compound annual growth rate estimate of 2.70 percent in peak demand over the next 20 years.

A dynamic error correction modeling approach is used to analyze El Paso County residential electricity usage. Short run departures from the long run consumption path may be attributable to income shocks, unexpected variations in climate, or other variables. Data constraints may hinder the ability to gain enough degrees of freedom for reliable parameter estimates in some markets. This study is able to include annualized data from 1977 to 2011 for El Paso County.

Depending on location, some regions of the United States do not offer a substitute good as an alternative energy source for electricity. For example, utilities that are able to generate electricity via hydroelectric plants observe lower costs per kilowatt hour, and substitute goods such as natural gas are usually not competitive. In the case of El Paso County, a substitute good is available. Natural gas is included in the model as a substitute good, although the data are not

as complete as for electricity. Estimates of the residential price for natural gas are simulated for the years 1982 to 1989.

Data constraints may also play a role in the decision whether to employ marginal electricity rates or average rates. Marginal rates for electricity usage are determined by negotiations between utility providers and utility regulators. Customer classes within a service territory may receive reduced rates, and block pricing can also come into play, depending on the quantity of electricity consumed. As a consequence of data constraints for El Paso Electric Company, the average price of electricity is employed.

The first econometric studies of the demand for electricity can be traced back to Houthakker (1951). The results of that study point to relatively strong sensitivity of electricity usage in response to changes in price and income (Dergaides and Tsoulfidis, 2008). More recent studies examine the determinants of electricity demand in both the short run, and the long run (Silk and Joutz, 1997). Empirical evidence repeated by Contreras et al. (2009) indicates negative income elasticity estimates for residential electricity consumption at the national level in the United States. One recent effort obtains similar results for the Seattle metropolitan economy (Fullerton et al., 2012). This study further examines this topic at the municipal level with data for El Paso County, Texas.

Chapter 2: Literature Review

Previous studies regarding the residential demand for electricity utilize both time series data and cross sectional data. Anderson (1973) utilizes a 1969 cross-section of the 50 states. That study attempts to improve predictive accuracy for residential electricity demand by taking into account the prevalence, at that time, of residential electricity rate schedules that provide quantity discounts. The marginal price of electricity is identified as the relevant determinant rather than average price. The estimated parameters exhibit the expected signs except for size of household. The price variable for electricity and the household income variable are found to be statistically significant at the 1-percent level.

One of the earliest studies to find that the long run own price elasticity of demand for electricity is at least unitary is Halvorsen (1975). That study utilizes cross sectional data and finds that the elasticities of demand estimated using average price measures are equal to those using marginal price data. Direct price elasticities are calculated from the structural demand equation using typical electric bill data. The study concludes that typical electric bill data adequately represent the marginal price schedule. All estimates of the own price elasticity fall within the range of -1.00 to -1.21, and are statistically significant at the 1-percent level.

Multi-step declining block pricing is addressed in a paper by Cicchetti and Smith (1975). The study identifies the issue of customers at different levels of consumption paying prices which are different on average than at their margin. The purpose of the paper is to examine model design and price measure so as to be able to avoid specification errors. Five separate price measures are included in both a dynamic demand model and a static demand model. Price measures include average revenue, the typical bill for 250, 500, and 750 kWh's, and the price for the second 250 kWh's of electric power. Although the study correctly points out that

adjustments for simultaneity may be necessary, average revenue is identified to be preferable as a price measure.

One of the earliest studies to distinguish between demand in the short run and demand in the long run is a survey study by Taylor (1975). In the short run, the stock of electricity consuming capital is fixed. In the long run, the stock of energy consuming capital is variable. The study assumes that, in the long run, a change in income leads to a revision of the desired stock of appliances. A change in the stock of appliances results in a divergence from the long run equilibrium. The study suggests that forces will be set into motion that will eliminate the divergence, and re-establish the long run equilibrium. The results of the survey study indicate that the price elasticity for electricity is much larger in the long run. The income elasticity is also much larger in the long run and ranges between 0.0 and 2.0 depending on the type of model used.

A re-examination of residential electricity demand is undertaken by Houthakker (1980) utilizing pooled cross-sectional and time series state level data. The study analyzes the method of calculating the marginal price of electricity. Previous work utilized typical electric bills for 750 and 1,000 kWh's that may have produced inconsistent estimates of price and income elasticities. This study utilizes a single estimate of the marginal price for the years 1964 to 1976 for each state. The results of the estimation are included with the 48 states combined, and a breakdown of four regions of the United States, as well. The combined national data yield coefficient estimates that are highly significant with the expected signs. Disposable income, marginal electricity price, and average gas price have elasticities of 1.78, -1.42, and 0.73, respectively. Substantial diversity in the income coefficients at the regional level is also documented.

Roth (1981) cites a failure in the existing empirical literature to deal with increasing block pricing. This study uses both marginal and average prices of electricity under a block pricing approach and determines that residential electricity is an inferior good. Most of the existing studies of electricity demand report positive income elasticities, where the demand for residential electricity increases with income. The "inferior" good designation results from the average price coefficient estimate. The indirect effect is established by the positive sign of the parameter for average price, which implies a reduction in real income. The effect of an increase in electricity demand in response to a reduction in real income indicates that electricity is an inferior good. This study utilizes monthly residential sales data for the period covering January 1974 to December 1977, and is conducted at the municipal level for an electric utility in the southwestern United States.

In a survey study of residential electricity, Archibald et al. (1982) examines seasonal variation in residential electricity demand. Twelve monthly electricity demand equations are estimated for 1975. The study hypothesizes the coefficients will be negative for price and positive, but small, for income. The anticipation of a small impact on electricity consumption in response to income is related to the static nature of the model. An increase in income is expected to increase the stock of appliances and have little effect on the intensity of use of the existing stock of appliances. The study assumes that electricity is probably not an inferior good. Empirical results indicate that income elasticities are low, ranging between 0.03 and 0.28, but positive and not seasonal. Short run price elasticities are found to be inelastic. The price elasticity of demand tends to be higher during peak demand months than in off-peak months.

The abundance of literature concerning the use of marginal price, average price, or both variables, is investigated by Shin (1985) utilizing a model that includes a price perception

variable. The study hypothesizes that consumers do not respond to marginal prices due to the high cost associated with determining what marginal block price the consumer is in at the time of consuming the electricity. The consumer is, therefore, assumed not to possess perfect knowledge concerning electricity prices, and is not as well informed as prior studies often assume. The study makes the point that consumers respond to the price of electricity through the negligible cost of reading their electric bill each month and, therefore, are responding to an ex post average price. Empirical results support the hypothesis that consumers respond to the average price of electricity as perceived from monthly electric bills.

Short run income elasticity of demand is examined in a survey study conducted by Branch (1993). Generalized least squares parameter estimation is utilized due to the correlation of the error terms which arises from the use of panel data. This study is national in scope and utilizes total annual expenditures as a proxy for permanent income. The generalized least squares estimate for income elasticity is 0.23 and -0.20 for price. Both of those estimates are statistically significant at the 1-percent level of confidence. Demographic characteristics of the estimation results indicate that monthly kWh usage is 8 percent higher per additional household member. The results also indicate that electricity consumption increases by 0.3 percent per year of age, implying that a person at age 65 averages 9 percent higher electricity consumption than a person at age 35. Housing unit size increases electricity consumption by 4 percent for each additional room.

In a study of five Southern states, Hsing (1994) estimates residential demand for electricity using a cross-sectional and time-wise autoregressive model. The study points out that many regional studies utilize pooled data in order to increase sample size, thereby reducing standard errors. A more careful analysis should also examine whether the error terms in different

states are correlated with each other. Covariances are found to be different from zero in many cases. Empirical results find that the price of the substitute good is insignificant in the OLS and uncorrected time series models, but is significant in the corrected time series model. Short run elasticities for price and income are found to be -0.239 and 0.397, while long run elasticities for price and income are found to be -0.543 and 0.902.

Silk and Joutz (1997) employ an error correction approach to model annual US residential electricity demand from 1949 to 1993. The study anticipates that alternative fuel prices will not have a very large impact on electricity consumption due to constraints on consumer ability to switch fuel sources. The results of the long run specification confirm that alternative fuel sources have a small effect on electricity consumption with an estimated coefficient of 0.0454. The short run model contains elasticities for price and income that are one-half of those found in the long run model. Long run elasticities for price and income are found to be -0.48 and 0.52. The error correction term coefficient is -0.37 and is statistically significant. The error correction coefficient value indicates that the short run deviation from the long run equilibrium will dissipate in approximately 2.7 years.

Narayan et al. (2007) estimates income and price elasticities for residential electricity demand in G7 countries. A panel co-integration technique is used that takes into account time series properties of the data. The study utilizes per capita income, own price, and a substitute good price as the explanatory variables in the model. Higher real income is expected to increase electricity consumption. The dependent variable is the natural log of per capita residential electricity consumption. The empirical results for the long run find an income elasticity of 0.31 and a price elasticity of -1.45. The elasticity of the substitute good price is 1.77. In the short

run, all of the estimated coefficients are found to be negative. However, none of the estimated coefficients in the short run are found to be statistically significant at the 5-percent level.

Dergiades and Tsoulfidis (2008) use per capita income, average price of electricity, price of oil, weather conditions, and the stock of occupied housing as the explanatory variables to estimate the demand for residential electricity. The stock of occupied housing is used as a proxy for the stock of household appliances. The study describes potential simultaneity bias when using a single equation to estimate electricity demand and deals with it by employing an autoregressive distributed lag approach. Results indicate that the coefficient for the stock of occupied housing is positive and significant. A one percent increase in the per capita occupied stock of housing leads to a 1.5 percent increase in per capita electricity consumption. All of the coefficients exhibit the hypothesized signs and are statistically significant. The long run income elasticity is found to be 0.27. In the short run, the income elasticity is much lower at 0.10. The coefficient for the error correction term is -0.363 and indicates short run departures from the long run equilibrium will dissipate in 2.75 years.

In a study of data covering all 50 states and the District of Columbia, Contreras et al. (2009) find that residential electricity is an inferior good. The study uses the average price of electricity, number of households, personal income, and weather conditions to estimate electricity demand. This study includes the use of dummy variables to identify nine regions of the United States. The coefficients for the dummy variables are not statistically significant. Those results indicate that different regions of the United States may contain similar demand characteristics for electricity and exhibit less heterogeneity than previous studies indicate.

The issue of whether to include marginal or average electricity prices has long been a source of debate (Cicchetti and Smith, 1975; Roth, 1981; Alberini et al., 2011). The absence of

perfect rates knowledge is what drives many researchers to use the average price of electricity in regression models (Shin, 1985). A survey by Faruqui et al. (2010) attempts to determine if consumption is altered when customers possess real time knowledge of the marginal price of the electricity they consume. Twelve utility pilot programs are evaluated in this study. The pilot programs involve the installation of In-Home Displays (IHDs) that give direct feedback of the price of electricity at the moment of consumption. Results indicate that energy savings range from three to thirteen percent when perfect knowledge of price is made available to the consumer. Due to time-constraints, the study is unable to determine if consumers respond to the increased knowledge initially, but then acclimate to the presence of the IHD, and ignore the real time price in the long run.

Empirical estimates of price and income elasticities can vary considerably. Bernard et al. (2011) report evidence that the variability in outcomes is due to the different types of data and methodologies used. Using household data from Quebec, statistically significant results are obtained that indicate highly elastic own-price and moderately inelastic cross-price elasticities for that region of Canada. In that study, neither short run nor long run income elasticities are significant at the 5-percent level.

In a nationwide study of the 50 largest metropolitan areas of the United States, Alberini et al. (2011) uses a mixed panel multi-year cross-section of households to study residential electricity demand from 1997 to 2007. The data used in this study cover more than 69,000 single family homes. Estimations are made for both a static and a dynamic model. The study finds a strong household response to energy prices. The static model estimates a price elasticity of -0.86 and the dynamic model estimates an elasticity of -0.74. Both coefficients are significant at the 1-percent level. The effect of income in the model is not as robust. The static model estimates an

income elasticity of 0.02 and the dynamic model estimates an elasticity of 0.01. Sample data utilized indicate that, as incomes rise, households choose less energy intensive appliances and homes.

The issue of certainty regarding the price of residential electricity demand is examined by Ito (2012). This study examines the possibility that consumers make sub-optimal choices with respect to residential electricity consumption by using the average price paid from their previous electric bill. The opposing theory is that consumers optimize consumption with respect to marginal price, or expected marginal price when pricing structures are uncertain. The empirical findings support strong evidence that consumers respond to the average price of electricity rather than marginal price. Estimation results from a model that includes both average price and marginal price find that the coefficient for average price is statistically significant, and the coefficient for marginal price is statistically insignificant. The study also finds that when marginal price and average price change in opposite directions, consumption of residential electricity responds to the average price. The study includes a graph of the distribution of consumption under a block pricing schedule. The histogram indicates there is no bunching around the block price parameters even when the marginal price increases by 80 percent around the second block price.

Recent empirical research of residential electricity consumption reports a long run negative income elasticity for Seattle, Washington (Fullerton et al., 2012). An error correction model is estimated using annual data for the years 1960 to 2007. Data for the study come from Seattle City Light, a public electric utility that employs an increasing block rate pricing schedule. Due to data constraints, the price variable employed is the average price of electricity per kilowatt hour consumed. The dependent variable is kilowatt hours consumed per residential

customer. The results of the estimation find that residential demand is price inelastic, and even more so in the short run. The long run co-integrating equation finds that the income elasticity is negative and statistically significant at the 1-percent level. This result indicates that electricity is an inferior good in Seattle. In the short run, electricity is treated as a normal good with a positive income elasticity. The error correction coefficient is found to be -0.192 and this coefficient implies that short run consumption deviations return to the long run equilibrium in 5.2 years.

Chapter 3: Data and Methodology

The data are from 1977 to 2011 and come from El Paso Electric Company filings with the Federal Energy Regulatory Commission (FERC). The dependent variable is residential electricity consumption measured in kilowatt hours (KWH) and the number of customers billed by El Paso Electric. As in a number of existing studies that examine the demand for residential electricity (Narayan et al., 2007; Hsing, 1994; Shin, 1985), this study includes the price of natural gas in the model in order to capture substitution effects.

There is a debate regarding whether the price variable for electricity should be the average price, the marginal price, or both. Recent evidence from a study by Ito (2012) finds that even when both average price and marginal price data are available, consumers respond to the average price. El Paso Electric currently utilizes a single block residential rate that includes a one cent increase per kilowatt hour for summer rates compared to the winter rate. As a result of recent empirical evidence that finds consumers respond to the average price, and due to a lack of detailed historical marginal rate schedules, this study employs average revenue per KWH as the price variable.

Per capita income is included in the model to account for income effects and cyclical economic conditions that influence residential energy consumption. Most prior empirical evidence, conducted at the state level, finds that electricity consumption is positively correlated to income. Per capita income data for El Paso County are obtained from the Bureau of Economic Analysis (BEA). The Consumer Price Index is used to deflate the price and income data that are used in the model to obtain real values indexed on 1982-1984 dollars.

The impact of weather is included in the model by using heating degree days (HDD) and cooling degree days (CDD). The HDD and CDD variables are based on a 65°F base in El Paso

County, and are obtained from El Paso Electric Company. Calculations for HDD and CDD are performed by the National Oceanic and Atmospheric Administration. Average temperatures for the day are calculated by adding the maximum temperature to the minimum temperature, and dividing by two. If the average temperature for the day is above 65°F, the difference is the number of CDD for that day. If the average temperature for the day is below 65°F, the difference is the number of HDD for that day.

This study will use an error correction model that is able to identify the speed at which short run departures will return to the long run equilibrium. Units of measure are identified and described in Table 1. Definitions of the variables utilized are also identified in Table 1.

Table 1 – Mnemonics and Definitions

Variable	**Definition**
KWHC	Kilowatt Hours per Residential Customer
YCAP	Real per Capita Income, Thousands U.S. Dollars, Base Period 1982-1984
PKWH	Price per Kilowatt Hour of Electricity, Real U.S. Dollars, Base Period 1982-1984
PGAS	Price per CCF of Natural Gas, Real U.S. Dollars, Base Period 1982-1984
HDD	Heating Degree Days- Sum of Avg. Daily Temperature Under 65° Base
CDD	Cooling Degree Days- Sum of Avg. Daily Temperature Above 65° Base
CSTM	Number of Residential Customers, Thousands
CPI	Consumer Price Index, National 1982-1984 Base Period
TRDC	Transmission & Distribution Capital Stock, Real U.S. Dollars, Base Period 1982-1984

This study follows the error correction techniques developed by Engle and Granger (1987) that allows parameter estimation for time series data that are co-integrated. A natural logarithmic transformation is applied, so that the parameters represent the elasticities of demand. The long run equation is specified below.

$$\begin{aligned} Ln(KWHC_t) = \lambda0 + &\underset{(+)}{\lambda1Ln(YCAP_t)} + \underset{(-)}{\lambda2Ln(PKWHt)} + \underset{(+)}{\lambda3Ln(PGAS_t)} + \underset{(+)}{\lambda4Ln(HDD_t)} \\ + &\underset{(+)}{\lambda5Ln(CDD_t)} + U_t \end{aligned} \qquad (1)$$

The equation specified above represents the long run relationship of how equilibrium per customer electricity consumption evolves over time. It is known as the co-integrating equation. The expected signs of the parameters are shown in the parentheses underneath the equation. A positive coefficient for the per capita income variable would indicate that electricity is a normal good. Many prior empirical studies based on state level data have found that an increase in income leads to an increase in the amount of residential electricity consumed, however; two recent studies report negative income elasticities for the demand of electricity (Contreras et al., 2009; Fullerton et al., 2012).

Increases in the price per KWH are expected to reduce the demand for residential electricity. If electricity and natural gas are substitutes, increases in the price of gas should lead to an increase in electricity consumption (Alberini et al., 2011). The coefficients for HDD and CDD are hypothesized to be positive due to the desire for more comfortable and healthy household environments during periods of low temperatures and high temperatures, respectively.

Short run departures from the long run equilibrium can be induced by a variety of factors. A change in income or a change in the price of electricity, among other possibilities, can cause short run departures relative to the long run equilibrium. The short run equation includes a difference operator. The specification for the short run equation is represented below. In Equation (2), d represents a first difference operator.

$$\underset{}{dLn(KWHC_t)} = \beta 0 + \underset{(+)}{\beta 1 dLn(YCAP_t)} + \underset{(-)}{\beta 2 dLn(PKWH_t)} + \underset{(+)}{\beta 3 dLn(PGAS_t)} + \underset{(+)}{\beta 4 dLn(HDD_t)}$$

$$+ \underset{(+)}{\beta 5 dLn(CDD_t)} + \underset{(-)}{\beta 6\, U_{t-1}} + V_t \qquad (2)$$

The residuals from the long run equation are lagged and included in the short run equation as the error correction term (U_{t-1}). The coefficient for the error correction term is expected to be negative, and indicates the rate at which the short term deviation will return to the long run equilibrium. The magnitude of the coefficient for the error correction term represents the speed of adjustment to any short run deviation from the long run equilibrium. For example, a coefficient value of negative one would indicate that the correction will be completed in one time period. The time required for total dissipation of the short run deviation increases as the value of the error term coefficient approaches zero.

Growth in the customer base of a utilities service area contributes to peak load demand and requires careful analysis to ensure sufficient generating capacity is online to service native load and reserve requirements. Accordingly, an equation is specified for growth in the average number of customers. The long run co-integrating equation for the residential customer base is specified below.

$$LnCSTM_t = c_0 + c_1Ln(POP_t) + c_2Ln(YCAP_{t-1}) + g_t \quad (3)$$

$$(+) \qquad (+)$$

In Equation (3) specified above, population (POP) is hypothesized to be positively correlated to growth in the customer base. Economic conditions are also hypothesized to be positively correlated to the customer base, and are represented in the model as El Paso Real per Capita Income (YCAP). The short run error correction specification includes a difference operator, and a lagged residual term from the long run regression. The short run specification is represented below.

$$dLnCSTM_t = f_0 + f_1dLn(POP_t) + f_2dLn(YCAP_{t-1}) + f_3g_{t-1} + h_t \quad (4)$$

$$(+) \qquad (+) \qquad (-)$$

Short run departures from the long run equilibrium may result from lag time in the construction of new homes, or migrant population increases that may not immediately result in new accounts for several periods. Any prior period deviation from the long run equilibrium is expected to partially dissipate in the subsequent period. The number of periods required to completely dissipate the deviation depends on the magnitude of the error correction coefficient.

Chapter 4: Empirical Results

Econometric models that include independent variables that are jointly determined with the dependent variable may contain simultaneity bias. Potential simultaneity is of concern in this study due to the fact that KWH consumed appears on both sides of Equation (1). A model that contains simultaneity bias will yield biased estimators and could lead to unreliable forecasts (Dergiades and Tsoulfidis, 2008).

Among several acceptable tests for identifying simultaneity is the artificial regression procedure (MacKinnon, 1992). The artificial regression test will verify if the average real price variable (PKWH) contains a bi-directional relationship with the dependent variable (KWHC). The null hypothesis is no endogenous relationship exists between the average price variable and the dependent variable.

The artificial regression test for the presence of simultaneity requires the identification of instrumental variables that are correlated with electricity price. The instrumental variable chosen for this test is the real national net capital stock of fixed assets for electric power transmission and distribution structures (TRDC) U.S. Dollars. El Paso Electric is a privately owned utility whose rates must be approved by the Public Utility Commission of Texas (PUCT). Privately owned utilities like El Paso Electric must submit rate case requests to the state utility commission based on the cost of operating and capital costs. Capital expenditures for transmission and distribution structures constitute a significant portion of the rate base schedule used to calculate end user residential rates for investor owned utilities.

The results of the artificial regression test indicate the null hypothesis that PKWH is not correlated with the error term in Equation 1, is rejected at the 1-percent level. Rejection of the

null hypothesis requires the estimation of a real price equation to obtain fitted values for electricity prices. The estimated price equation is represented below as Equation (5).

$$PKWH_t = C_0 + C_1(PGAS_t) + C_2(YCAP_t) + C_3(HDD_t) + C_4(CDD_t) + C_5(TRDC_t) + m_t \quad (5)$$

The specification of the real price equation includes the instrumental variable used in the artificial regression test (TRDC), as well as the exogenous variables from Equation (1). Fitted values for electricity prices (PKWHAT) are obtained from Equation (5), and provide the inflation adjusted average price measure used in the long run demand equation. The modified long run demand equation is shown below as Equation (6).

$$Ln(KWHC_t) = \lambda_0 + \lambda_1 Ln(PKWHAT_t) + \lambda_2 Ln(PGAS_t) + \lambda_3 Ln(YCAP_t) + \lambda_4 Ln(HDD_t) + \lambda_5 Ln(CDD_t) + u_t \quad (6)$$

Table 2 displays the estimation results for the long run co-integrating demand Equation (6). All of the estimated coefficients contain the expected sign except for per capita income. A negative coefficient for per capita income indicates that residential electricity in El Paso County is treated as an inferior good. That result runs contrary to many earlier studies of residential electricity demand. The long run equation allows for upgrades in the stock of appliances as incomes rise, and the upgrade may account for an increase in the energy efficiency of new homes and appliances. The estimated coefficient indicates that a 1-percent increase in real per capita income decreases residential electricity usage by 0.47%. One earlier study that also report negative income elasticities for residential electricity demand is Contreras et al. (2009). That

study examines state level data across the United States. A much earlier study by Roth (1981), and a more recent regional study by Fullerton et al. (2012), also report negative income elasticities for residential electricity demand.

All of the coefficient estimates are significant at the 5-percent level, except heating degree days (HDD). The insignificant coefficient for heating degree days may be attributable to the warm desert southwest climate that is prevalent to El Paso County. The coefficient of determination indicates the model is a good fit with an R-squared value of 89.3 percent. The coefficient of determination measures how well the explanatory variables describe the variation in the dependent variable about its mean.

Table 2 – Long Run Demand Equation for Kilowatt Hours per Capita

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 02/04/13 Time: 15:38
Sample: 1977 2011
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.047687	0.716163	9.840904	0.0000
LOG(PKWHAT)	-0.691545	0.131691	-5.251280	0.0000
LOG(PGAS)	0.131366	0.025845	5.082884	0.0000
LOG(YCAP)	-0.471265	0.150962	-3.121744	0.0040
LOG(HDD)	0.036255	0.057443	0.631138	0.5329
LOG(CDD)	0.112181	0.052271	2.146135	0.0404

R-squared	0.893763	Mean dependent var	8.734473
Adjusted R-squared	0.875446	S.D. dependent var	0.077235
S.E. of regression	0.027258	Akaike info criterion	-4.212127
Sum squared resid	0.021547	Schwarz criterion	-3.945496
Log likelihood	79.71223	Hannan-Quinn criter.	-4.120086
F-statistic	48.79480	Durbin-Watson stat	0.838736
Prob(F-statistic)	0.000000		

Although the overall estimation results in Table 2 are favorable, the Durbin-Watson statistic indicates that the residuals are positively correlated. Alternative specifications using

autoregressive and moving average coefficients may improve the long run estimation results. A review of the correlogram of the residuals helps to identify the number of lag periods to apply to the autoregressive and moving average coefficients. After experimenting with several alternative specifications, superior results were obtained by the estimation of Equation (7) shown below. Results for the alternative specifications are included in the appendix. Due to the insignificant results reported earlier for heating degree days, that variable is removed from the equation.

$$Ln(KWHC_t) = \lambda_0 + \lambda_1 Ln(PKWHAT_t) + \lambda_2 Ln(PGAS_t) + \lambda_3 Ln(YCAP_t) + \lambda_4 Ln(CDD_t) + MA(1) + u_t \quad (7)$$

The estimation results for Equation (7) are displayed in Table 3. All of the coefficient estimates are significant at the 5-percent level. The Durbin-Watson statistic no longer indicates that the residuals are positively correlated. The coefficient of determination increases to 92.4 percent. The real average price of electricity (PKWHAT) exhibits the expected sign and is fairly responsive to variations in the real price of electricity with an elasticity coefficient of -0.56. The price elasticity is in the middle of a range of other price elasticities reported in similar studies (Alberini et al., 2011; Espey and Espey, 2004.)

Table 3 – Long Run Demand Equation Employing Moving Average Coefficient

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 02/04/13 Time: 15:46
Sample: 1977 2011
Included observations: 35
Convergence achieved after 13 iterations
MA Backcast: 1976

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.162703	0.262811	27.25424	0.0000
LOG(PKWHAT)	-0.560698	0.146041	-3.839310	0.0006
LOG(PGAS)	0.119302	0.031997	3.728541	0.0008
LOG(YCAP)	-0.365877	0.177609	-2.060018	0.0485
LOG(CDD)	0.144462	0.032143	4.494412	0.0001
MA(1)	0.730475	0.130099	5.614775	0.0000

R-squared	0.924914	Mean dependent var	8.734473
Adjusted R-squared	0.911968	S.D. dependent var	0.077235
S.E. of regression	0.022916	Akaike info criterion	-4.559171
Sum squared resid	0.015229	Schwarz criterion	-4.292540
Log likelihood	85.78549	Hannan-Quinn criter.	-4.467130
F-statistic	71.44502	Durbin-Watson stat	2.026801
Prob(F-statistic)	0.000000		

Inverted MA Roots	-.73

The real price of natural gas, included in the model to capture substitute good effects, has an estimated coefficient that is positive and statistically significant at the 1-percent level. The cross price elasticity for the price of natural gas is 0.11, indicating that natural gas is an imperfect substitute good for electricity in El Paso. The cross price elasticity reported above is smaller in magnitude than those reported in similar studies that report cross price elasticities that range from 0.22 to 0.32 (Roth, 1981; Hsing, 1994). The smaller cross price elasticities reported herein may reflect the development of new consumer plug in products over the past three decades. Since 1981, the share of residential electricity used by appliances and electronics has nearly doubled from 17 percent to 31 percent (Hojjati and Wade, 2012). Most of the newly developed

consumer electronics products cannot use energy sources other than electricity, thus reducing the overall substitutability of natural gas in residences and businesses.

As expected, the explanatory variable representing cooling degree days (CDD) is positively correlated to residential electricity demand. Summer temperatures commonly reach above 100 degrees, and peak annual demand on El Paso Electric's system is always in the summer months. A 1-percent increase in annual cooling degree days (CDD) increases residential usage by approximately 0.14%. The coefficient representing real per capita income remains to be negative, and again signifies that electricity is treated as an inferior good in El Paso County.

Estimation of the short run equation includes a difference operator and a lagged error correction term (ST). The error correction term is the residual series from the long run equation, and represents the deviations from the long run equilibrium. Estimation results for the short run equation are shown in Table 4.

Table 4 – Short Run Demand Equation for Kilowatt Hours per Capita

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 02/26/13 Time: 18:20
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006033	0.004802	1.256391	0.2194
DLOG(PKWHAT)	-0.146402	0.176168	-0.831038	0.4130
DLOG(PGAS)	0.036011	0.042341	0.850507	0.4023
DLOG(YCAP)	-0.311832	0.228071	-1.367259	0.1824
DLOG(CDD)	0.151956	0.037041	4.102364	0.0003
ST(-1)	-0.206588	0.181407	-1.138805	0.2644

R-squared	0.488916	Mean dependent var	0.005784
Adjusted R-squared	0.397651	S.D. dependent var	0.027394
S.E. of regression	0.021261	Akaike info criterion	-4.705139
Sum squared resid	0.012656	Schwarz criterion	-4.435781
Log likelihood	85.98736	Hannan-Quinn criter.	-4.613280
F-statistic	5.357108	Durbin-Watson stat	1.779455
Prob(F-statistic)	0.001407		

All of the estimated coefficients have the expected sign, except for real per capita income. The real per capita income (YCAP) coefficient is negative, a counter-intuitive result. The real per capita income coefficient is not statistically significant, implying there are not any reliable real income effects on residential electricity consumption in the short run.

The only statistically significant short run coefficient at the 5-percent level in Table 4 is that for cooling degree days (CDD). This result indicates that, in the short run, weather is the best explanatory variable for residential electricity consumption. High temperatures for El Paso County were above 90 degrees from April through October in 2011, according to the National Oceanic and Atmospheric Administration. During the month of June 2011, there were 21 days when the temperature exceeded 100 degrees. The insignificant results reported for the own price and cross price elasticities indicates that, in the short run, consumers do not respond to changes in prices.

As hypothesized, the sign for the error correction parameter is less than zero. The magnitude of the error correction coefficient is -0.20 and this represents the speed of adjustment for consumption to return to the long run equilibrium. The error correction parameter reported in Table 4 indicates that approximately 20% of the consumption deviation from the long run equilibrium is rectified during the first year. A total of approximately 4.8 years are required to completely dissipate a consumption error.

For investor owned utilities like El Paso Electric, anticipating growth in the service territory is important in order to successfully maintain sufficient generation capacity. Capital expansion projects that include transmission and distribution, as well as generation, must be planned and accurately forecasted. Rights of way for transmission poles and substations require lengthy regulatory and environmental permitting requirements. Understanding residential

customer growth is part of the forecasting process and requires a model that incorporates both demographic and economic factors. The long run specification in Equation (3) above incorporates both factors, estimation results are shown in Table 5.

Table 5 - Long Run Co-Integrating Equation for EPE Residential Customer Base

Dependent Variable: LOG(CSTM)
Method: Least Squares
Date: 02/20/13 Time: 19:04
Sample (adjusted): 1982 2011
Included observations: 30 after adjustments
Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.010615	1.004683	2.001242	0.0559
LOG(POP)	0.348977	0.141527	2.465793	0.0206
LOG(YCAP(-1))	0.480065	0.089938	5.337713	0.0000
AR(4)	0.767706	0.050911	15.07944	0.0000

R-squared	0.995410	Mean dependent var	5.256118
Adjusted R-squared	0.994880	S.D. dependent var	0.186795
S.E. of regression	0.013366	Akaike info criterion	-5.668669
Sum squared resid	0.004645	Schwarz criterion	-5.481843
Log likelihood	89.03003	Hannan-Quinn criter.	-5.608902
F-statistic	1879.400	Durbin-Watson stat	1.282456
Prob(F-statistic)	0.000000		

Inverted AR Roots	.94	.00-.94i	.00+.94i	-.94

The estimation results exhibit favorable statistical characteristics. All of the coefficient estimates are significantly different from zero at the 5-percent level. The coefficient of determination indicates that 99 percent of the variation in the dependent variable is explained in the equation. As expected, both coefficients also display a positive relationship with customer growth. The magnitude of the coefficient for population indicates that a 1-percent increase in population growth leads to a 0.34% increase in the customer base. A one period lag is applied to the real per capita income variable, and the estimated coefficient indicates a 1-percent increase in real per capita income leads to a 0.48% increase in the EPE customer base. Increases in real per

capita income may influence customer accounts by increasing the rate of metropolitan household formation and the establishment of new residences.

Results for the short run error correction equation for customer growth are shown in Table 6. The empirical results for the short run equation reflect the difficulty in modeling customer growth in the short run. However, the positive and significant results for the constant term indicate that customer growth is steadily increasing in El Paso County. The estimated coefficient for the constant term indicates that, holding all other variables constant, the number of customer accounts increases by approximately 0.02% per year.

The estimated short run coefficient for population contains the expected sign, but does not satisfy the 5-percent significance criterion. The population coefficient reported in this study is estimated at 0.29. A similar study conducted in the Pacific Northwest (Fullerton et al., 2012) reports an estimated coefficient of 0.10 for the population variable in the customer base equation. The magnitude of the estimated population coefficient herein indicates that population increases in El Paso have approximately three times as much impact on the customer account base than in Seattle. Immigration accounts for a much higher percentage of population growth in Seattle than it does in El Paso (Conway and Pedersen, 2013; Fullerton and Walke, 2012). Immigration will generally, if not always, have a greater impact on utility customer bases than population change related to natural causes. Given that, the parameter estimate shown for population in Table 6 is probably unreliably large.

Table 6 – **Short Run Equation for EPE Residential Customer Base**

Dependent Variable: D(LOG(CSTM))
Method: Least Squares
Date: 02/20/13 Time: 19:41
Sample (adjusted): 1983 2011
Included observations: 29 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018244	0.005691	3.205849	0.0037
D(LOG(POP))	0.297167	0.312881	0.949777	0.3513
D(LOG(YCAP(-1)))	-0.003906	0.103183	-0.037857	0.9701
JT(-1)	-0.281130	0.152424	-1.844398	0.0770

R-squared	0.154373	Mean dependent var	0.022934
Adjusted R-squared	0.052898	S.D. dependent var	0.009457
S.E. of regression	0.009203	Akaike info criterion	-6.411080
Sum squared resid	0.002117	Schwarz criterion	-6.222488
Log likelihood	96.96067	Hannan-Quinn criter.	-6.352016
F-statistic	1.521291	Durbin-Watson stat	0.547775
Prob(F-statistic)	0.233432		

The negative sign for lagged real per capita income is not expected, however, the computed t-statistic is not significantly significant. The error correction term is negative and less than one, as hypothesized. The magnitude of the error correction term indicates that approximately 28.1% of the adjustment toward long run equilibrium occurs in the first year following a deviation from it. A total of 3.5 years is required to fully dissipate any deviation from the long run equilibrium.

Major decisions by executive management regarding increases to generation capacity require customer demand forecasts. As an additional step towards examining the empirical results reported in this study, a 3-period out-of-sample forecast is simulated for residential KWH's consumed and customer growth. Compound annual growth rates (CAGR) are calculated from observed historical data for El Paso Electric, and include the period from 2001 to 2011. The CAGR's and the 3-year forecasted values for the explanatory variables are shown below in

Table 7. The forecasted weather variable does not utilize CAGR's, and is instead calculated by utilizing a 10-year historical mean value of 2,616 for CDD.

Table 7 – Explanatory Variable Growth

	PKWHAT	PGAS	YCAP	CDD	POP
10 YR CAGR	**-3.98**	**-2.94**	**1.65**	**0.000**	**1.76**
Year 1	0.043	0.200	13.597	2616	835.263
Year 2	0.042	0.194	13.882	2616	849.991
Year 3	0.040	0.188	14.050	2616	864.978

The 10-year CAGR for the fitted price variable, PKWHAT is -3.98%, and indicates that the real price of electricity has been declining over the past 10 years. The real price of natural gas also experienced declining prices over the same period with a CAGR of -2.94%. Real per capita income has a CAGR of 1.65%, and the CAGR for population growth is calculated at 1.76%. Table 8 reports the forecasts for the dependent variables and the year over year percentage changes.

Table 8 – EPE Residential Consumption and Customer Forecasts

Consumption and Customer Forecast						
YEAR	**KWHC**	**% Δ**	**MWH**	**% Δ**	**CSTM**	**% Δ**
Year 1	7,459	-	1,942,764	-	260,459	-
Year 2	7,483	0.32	1,983,945	2.12	265,127	1.79
Year 3	7,616	1.78	2,067,135	4.19	271,420	2.37

Due to the magnitude of the real price decline for electricity, kilowatt hour sales are forecasted to grow from 7,459 in Year 1 to 7,616 in Year 3. The effects of the real price decline outweigh the impacts of the real income growth, even when combined with a decline in the price of a substitute good. The robust impact for electricity price may indicate that even if the negative income elasticities reported in this study hold true, residential demand could continue to grow if the price of electricity continues to fall.

Using the data reported in Table 8, the forecast implies that total residential sales would increase by a compound annual growth rate of 3.15% for the 3-year period. The observed historical 10-year compound annual growth rate for EPE residential sales is approximately 3.81%. El Paso Electric reported residential GWH usage for 2012 to be 1,975 while the out of sample forecast predicted GWH usage to be 1,942. The simulation results indicate that the forecasting ability of the model is within a reasonable expectation of accuracy.

Employing a constant value for weather implies that the out of sample forecast would not capture any of the possible effects due to global warming. The Earth has been growing warmer over the last 50 years, and the past decade was the warmest on record (Arndt, Baringer, and Johnson, 2010). An increase of one degree Fahrenheit in average yearly temperature in El Paso County would increase total cooling degree days by approximately 211 days per year. A three year incremental distribution of the potential effects from a one degree increase in average temperature would increase the CDD variable in the first year from 2,616 to 2,686. The increase for the second year would grow the cooling degree days variable from 2,686 to 2,757. The third year of the distribution would include the entire 211 cooling degree day increase and would raise the CDD variable from 2,757 to 2,827. The increments in CDD would increase KWHC in Year 1 from 7,459 to 7,488. Kilowatt hours consumed would increase in Year 2 from 7,483 to 7,541

and Year 3 would see an increase from 7,616 to 7,705. The potential impacts due to global warming in the third year represent a 1.17 percent increase in KWHC due to the higher ambient temperature.

Public policy makers often work together with electric utility companies in order to promote energy conservation and energy efficiency. El Paso Electric offers incentives to homeowners for improvements in energy efficiency such as new windows and better insulation. As shown in Table 3, the elasticity of EPEC per capita residential electricity consumption with respect to price is -0.561. That implies that any serious efforts to induce greater energy conservation in El Paso will have to entail rate hikes. The latter is not surprising. The central role of price changes with respect to residential electricity usage is abundant and well documented (Anderson, 1973; Reiss and White, 2008).

On that basis, prospects for electricity conservation in El Paso are not very promising. The average EPEC residential real price for electricity has failed to keep pace with inflation for three consecutive decades. By 2011, the last year in the sample period, the residential real price per kilowatt hour was 51.1 percent below its level in 1983. Although numerous factors have influenced the evolution of electricity rates in El Paso, if the trend towards lower real prices for electricity continues, per capita residential electricity usage is likely to continue to increase in this portion of the EPEC service area.

Regulating residential energy usage through pricing policies could prove to be an effective tool for policymakers. Although the potential for regulating residential energy use through price increases may not be as straightforward as it appears. The El Paso City Council claimed rates were too high in 2011 and requested rate relief from El Paso Electric (Schladen, 2011). This request came at a time of capital expansion projects totaling more than $1 billion

over the next five years for El Paso Electric (Shockley and Heitz, 2012). Public controversy over high rates neutralizes the most effective tool for increased efficiency. In the absence of rate increases, aggregate residential electricity consumption in El Paso is likely to increase substantially.

Chapter 5: Conclusion

Residential electricity demand in El Paso County is analyzed in this study. Dynamic error correction models are estimated for average household consumption and the number of residential customer accounts. Among other things, error correction models estimate the speed at which long run equilibria are re-attained. Short run departures from the long run equilibrium may occur due to changes in income, changes in prices, and a variety of other factors. Explanatory variables for this study include the average real price of electricity, the real price of natural gas, real income, and weather.

The price variable for electricity is average cents per kilowatt hour. Because kilowatt hours consumed appears on both sides of the equation, an endogeneity test is performed. The presence of simultaneity between consumption and the price variable is confirmed using an artificial regression test. As a result of the test, fitted price values are obtained from an equation employing the use of an instrumental variable. Average fitted price values are utilized for the long run and short run per customer consumption equations.

All of the long run co-integrating demand equation coefficients are statistically significant at the 5-percent level. All of the estimated coefficient signs are as hypothesized except for per capita income. The income elasticity reported in this study is -0.36 and indicates that household electricity behaves similar to an inferior good in El Paso County. The negative income elasticity result runs counter to many studies, but has been documented for other regions in the United States. The error correction short run demand equation also reports a negative income elasticity coefficient; however, the computed t-statistic for that parameter estimate is not significantly different from zero at the 5-percent level.

This study reports an own price elasticity for residential electricity of -0.56, indicating that residential consumers in El Paso County respond to changes in electricity prices in an inelastic manner. The inelastic own price elasticity results reported in this study is comparable to price elasticities reported in similar studies. The estimated coefficient for the price of natural gas, the substitute good, is 0.12 and is significant at the 5-percent level. That result indicates that natural gas is an imperfect substitute for residential electricity in El Paso County.

Variables representing climate in the model are cooling degree days and heating degree days. The coefficients for heating degree days are insignificant and this regressor is dropped from the equation. The estimated coefficient for cooling degree days is 0.14 and is statistically significant at the 5-percent level. Cooling degree days are the only statistically significant coefficient reported in the short run equation. In the short run, weather clearly influences residential electricity consumption in this metropolitan economy.

As an additional model verification step, a 3-period out of sample forecast is simulated for average kilowatt hours consumed and customer growth. Taken together, the results of the forecast compare well to the historical growth rate for aggregate residential demand in the El Paso Electric service territory. The out of sample forecast indicates that total residential kilowatt hours consumed will grow at a compound annual growth rate of 3.15 percent over the next three years.

The negative long run income elasticity reported in this study is a provocative result and should encourage additional research at the regional level. One possible explanation for a decline in usage as incomes rise is the adoption of energy efficiency upgrades to appliances and homes in recent years. Reductions in residential electricity demand as increases in per capita

income occur should place less pressure on existing generation capacity, even as the regional economy continues to expand.

El Paso Electric has experienced steady growth in its customer account base, and has submitted applications to the Public Regulatory Commission to expand local generating capacity. This study indicates that public authorities could potentially use rate setting as a tool to reduce the demand for electricity, and therefore, reduce the need for El Paso Electric to expand local generating capacity. There is no evidence that public authorities representing the City of El Paso have considered using pricing policies to curtail residential electricity demand. In 2011, El Paso City Council requested rate relief from El Paso Electric. As reported above, lower residential electricity prices lead to increases in aggregate demand.

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Appendix I

Year	Kilowatt Hours per Residential Customer	Price per Kilowatt Hour of Electricity	Price per CCF of Natural Gas	Real per Capita Income	Heating Degree Days	Cooling Degree Days	Number of Residential Customers	El Paso County Population
1977	6,281	0.069	0.196	7.958	2,581	2,240	110.285	450.000
1978	6,173	0.079	0.154	8.129	2,350	2,356	115.619	460.600
1979	5,825	0.081	0.194	8.180	2,991	2,157	125.384	472.300
1980	6,087	0.084	0.219	7.935	2,647	2,509	124.34	479.899
1981	5,895	0.095	0.248	8.471	2,234	2,362	127.577	497.523
1982	5,889	0.096	0.258	8.365	2,582	2,373	131.341	511.892
1983	5,645	0.106	0.269	8.560	2,741	2,179	139.734	521.038
1984	5,556	0.104	0.266	8.830	2,724	2,106	145.409	529.668
1985	5,573	0.095	0.246	9.014	2,846	1,940	149.911	538.809
1986	5,555	0.092	0.182	9.180	2,593	2,025	154.753	549.592
1987	5,686	0.078	0.160	9.050	3,012	1,816	159.982	559.479
1988	5,883	0.076	0.157	9.145	2,699	1,834	163.188	568.804
1989	6,014	0.074	0.151	9.337	2,469	2,239	167.078	580.982
1990	5,979	0.071	0.180	9.439	2,484	2,221	170.267	591.610
1991	5,948	0.071	0.152	9.109	2,538	1,899	173.546	608.206
1992	6,033	0.076	0.127	9.627	2,475	2,432	176.591	619.138
1993	6,021	0.071	0.160	9.617	2,227	2,612	180.705	634.044
1994	6,181	0.070	0.134	9.747	2,082	3,067	184.572	646.181
1995	5,928	0.069	0.098	9.859	1,934	2,367	188.394	654.250
1996	6,111	0.067	0.143	9.949	2,335	2,572	191.235	656.482
1997	6,148	0.067	0.175	10.306	2,737	2,452	194.702	665.066
1998	6,161	0.067	0.134	10.610	2,521	2,490	198.443	671.250
1999	6,108	0.061	0.146	10.619	2,192	2,235	202.741	675.397
2000	6,398	0.059	0.233	10.958	2,376	2,679	207.184	679.622
2001	6,384	0.063	0.278	11.354	2,476	2,601	210.513	689.163
2002	6,507	0.062	0.198	11.720	2,460	2,701	214.536	696.446
2003	6,563	0.060	0.262	11.642	2,233	2,695	219.273	705.200
2004	6,518	0.058	0.297	11.771	2,545	2,327	224.514	717.652
2005	6,728	0.058	0.369	12.025	2,176	2,549	229.591	728.095
2006	6,620	0.066	0.342	12.261	2,020	2,457	234.802	744.795
2007	6,875	0.059	0.367	12.546	2,286	2,512	238.851	755.578
2008	6,741	0.057	0.387	12.695	2,188	2,272	242.465	769.930
2009	7,036	0.056	0.246	12.712	2,142	2,768	246.908	786.759
2010	7,419	0.054	0.239	13.201	2,273	2,738	251.669	800.647
2011	7,646	0.052	0.206	13.376	2,402	3,141	255.416	820.790

Units of measure:

Kilowatt Hours per Residential Customer – Kilowatt Hours

Price per Kilowatt Hour of Electricity – Constant 1982-1984 US$

Price per CCF of Natural Gas – Constant 1982-1984 US$

Real per Capita Income – Thousands, Constant 1982-1984 US$

Heating Degree Days – Sum of Avg. Daily Temperature Under 65° Base

Cooling Degree Days – Sum of Avg. Daily Temperature Above 65° Base

Number of Residential Customers – Thousands

El Paso County Population - Thousands

Data Source:

Kilowatt Hours per Residential Customer, Price per Kilowatt Hour of Electricity – El Paso Electric Company FERC Form-1 Filings

Price per CCF of Natural Gas – Texas Gas Service

Real per Capita Income – Bureau of Economic Analysis CA04

Heating Degree Days, Cooling Degree Days – El Paso Electric Company

Number of Residential Customers – El Paso Electric Company FERC Form-1 Filings

El Paso County Population – US Bureau of Census

Appendix II: CPI Deflated KWHC Equation Alternative Estimation Results

Table 9: Long Run KWHC Equation Alternative Employing Moving Average Coefficient

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 03/07/13 Time: 19:43
Sample: 1977 2011
Included observations: 35
Convergence achieved after 12 iterations
MA Backcast: 1976

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.660793	0.481124	13.84422	0.0000
LOG(PKWHAT)	-0.609565	0.149794	-4.069355	0.0003
LOG(PGAS)	0.125800	0.032064	3.923398	0.0005
LOG(YCAP)	-0.402509	0.178314	-2.257307	0.0320
LOG(HDD)	0.059687	0.048470	1.231416	0.2284
LOG(CDD)	0.144741	0.033417	4.331397	0.0002
MA(1)	0.691413	0.141514	4.885832	0.0000

R-squared	0.928773	Mean dependent var	8.734473
Adjusted R-squared	0.913510	S.D. dependent var	0.077235
S.E. of regression	0.022714	Akaike info criterion	-4.554790
Sum squared resid	0.014446	Schwarz criterion	-4.243720
Log likelihood	86.70882	Hannan-Quinn criter.	-4.447409
F-statistic	60.85175	Durbin-Watson stat	1.839522
Prob(F-statistic)	0.000000		

Inverted MA Roots	-.69

Table 10: Short Run KWHC Equation Alternative

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 19:52
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005300	0.004838	1.095542	0.2830
DLOG(PKWHAT)	-0.259825	0.205160	-1.266454	0.2162
DLOG(PGAS)	0.054717	0.045700	1.197308	0.2416
DLOG(YCAP)	-0.402553	0.242737	-1.658394	0.1088
DLOG(HDD)	0.047225	0.044097	1.070920	0.2937
DLOG(CDD)	0.146347	0.037314	3.922074	0.0005
ST(-1)	-0.145487	0.189716	-0.766870	0.4498

R-squared	0.509741	Mean dependent var	0.005784
Adjusted R-squared	0.400794	S.D. dependent var	0.027394
S.E. of regression	0.021205	Akaike info criterion	-4.687914
Sum squared resid	0.012141	Schwarz criterion	-4.373664
Log likelihood	86.69454	Hannan-Quinn criter.	-4.580746
F-statistic	4.678818	Durbin-Watson stat	1.923857
Prob(F-statistic)	0.002205		

Table 11: Long Run KWHC Equation Alternative: No HDD

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 03/07/13 Time: 19:30
Sample: 1977 2011
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.439248	0.354146	21.00619	0.0000
LOG(PKWHAT)	-0.687543	0.130212	-5.280171	0.0000
LOG(PGAS)	0.132447	0.025528	5.188318	0.0000
LOG(YCAP)	-0.475658	0.149282	-3.186315	0.0034
LOG(CDD)	0.101059	0.048715	2.074485	0.0467

R-squared	0.892304	Mean dependent var	8.734473
Adjusted R-squared	0.877944	S.D. dependent var	0.077235
S.E. of regression	0.026983	Akaike info criterion	-4.255628
Sum squared resid	0.021843	Schwarz criterion	-4.033435
Log likelihood	79.47349	Hannan-Quinn criter.	-4.178927
F-statistic	62.14017	Durbin-Watson stat	0.923603
Prob(F-statistic)	0.000000		

Table 12: Short Run KWHC Equation Alternative: No HDD

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 03/17/13 Time: 15:11
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006033	0.004802	1.256391	0.2194
DLOG(PKWHAT)	-0.146402	0.176168	-0.831038	0.4130
DLOG(PGAS)	0.036011	0.042341	0.850507	0.4023
DLOG(YCAP)	-0.311832	0.228071	-1.367259	0.1824
DLOG(CDD)	0.151956	0.037041	4.102364	0.0003
ST(-1)	-0.206588	0.181407	-1.138805	0.2644

R-squared	0.488916	Mean dependent var	0.005784
Adjusted R-squared	0.397651	S.D. dependent var	0.027394
S.E. of regression	0.021261	Akaike info criterion	-4.705139
Sum squared resid	0.012656	Schwarz criterion	-4.435781
Log likelihood	85.98736	Hannan-Quinn criter.	-4.613280
F-statistic	5.357108	Durbin-Watson stat	1.779455
Prob(F-statistic)	0.001407		

Table 13: Long Run KWHC Equation Alternative: No PGAS

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 19:21
Sample: 1977 2011
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.997949	0.927106	6.469541	0.0000
LOG(PKWHAT)	-0.156816	0.107097	-1.464239	0.1535
LOG(YCAP)	0.174616	0.110191	1.584665	0.1235
LOG(HDD)	0.055612	0.077491	0.717656	0.4785
LOG(CDD)	0.190965	0.067491	2.829485	0.0082

R-squared	0.799117	Mean dependent var	8.734473
Adjusted R-squared	0.772333	S.D. dependent var	0.077235
S.E. of regression	0.036852	Akaike info criterion	-3.632224
Sum squared resid	0.040743	Schwarz criterion	-3.410032
Log likelihood	68.56393	Hannan-Quinn criter.	-3.555524
F-statistic	29.83525	Durbin-Watson stat	0.475323
Prob(F-statistic)	0.000000		

Table 14: Short Run KWHC Equation Alternative: No PGAS

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 19:59
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007005	0.004659	1.503521	0.1439
DLOG(PKWHAT)	-0.033511	0.080378	-0.416914	0.6799
DLOG(YCAP)	-0.229648	0.196611	-1.168032	0.2526
DLOG(HDD)	0.027045	0.041064	0.658607	0.5155
DLOG(CDD)	0.165872	0.033820	4.904522	0.0000
ST(-1)	-0.154891	0.191015	-0.810885	0.4243

R-squared	0.483711	Mean dependent var	0.005784
Adjusted R-squared	0.391516	S.D. dependent var	0.027394
S.E. of regression	0.021369	Akaike info criterion	-4.695005
Sum squared resid	0.012785	Schwarz criterion	-4.425647
Log likelihood	85.81509	Hannan-Quinn criter.	-4.603146
F-statistic	5.246634	Durbin-Watson stat	1.684326
Prob(F-statistic)	0.001599		

Table 15: Long Run KWHC Equation Alternative: No HDD & No PGAS

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 19:39
Sample: 1977 2011
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.587915	0.425258	15.49156	0.0000
LOG(PKWHAT)	-0.143868	0.104738	-1.373606	0.1794
LOG(YCAP)	0.176039	0.109308	1.610485	0.1174
LOG(CDD)	0.174830	0.063136	2.769083	0.0094

R-squared	0.795669	Mean dependent var	8.734473
Adjusted R-squared	0.775895	S.D. dependent var	0.077235
S.E. of regression	0.036563	Akaike info criterion	-3.672345
Sum squared resid	0.041443	Schwarz criterion	-3.494591
Log likelihood	68.26604	Hannan-Quinn criter.	-3.610985
F-statistic	40.23816	Durbin-Watson stat	0.486633
Prob(F-statistic)	0.000000		

Table 16: Short Run KWHC Equation Alternative: No HDD & No PGAS

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 20:16
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007106	0.004611	1.541038	0.1341
DLOG(PKWHAT)	-0.009331	0.070802	-0.131788	0.8961
DLOG(YCAP)	-0.208447	0.192055	-1.085353	0.2867
DLOG(CDD)	0.165157	0.033471	4.934308	0.0000
ST(-1)	-0.193712	0.179910	-1.076716	0.2905

R-squared	0.475713	Mean dependent var	0.005784
Adjusted R-squared	0.403397	S.D. dependent var	0.027394
S.E. of regression	0.021159	Akaike info criterion	-4.738456
Sum squared resid	0.012983	Schwarz criterion	-4.513991
Log likelihood	85.55375	Hannan-Quinn criter.	-4.661907
F-statistic	6.578296	Durbin-Watson stat	1.633037
Prob(F-statistic)	0.000678		

Appendix III: PCE Deflated KWHC Equation Alternative Estimation Results

Table 17: PCE Deflated Long Run KWHC Equation Results

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 20:27
Sample: 1977 2011
Included observations: 35

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.883479	0.701876	9.807253	0.0000
LOG(PCKWHAT)	-0.666949	0.113090	-5.897503	0.0000
LOG(PCGAS)	0.125757	0.023385	5.377654	0.0000
LOG(PCYCAP)	-0.234643	0.082991	-2.827318	0.0084
LOG(HDD)	0.032350	0.057183	0.565731	0.5759
LOG(CDD)	0.135708	0.049989	2.714769	0.0111

R-squared	0.895194	Mean dependent var	8.734473
Adjusted R-squared	0.877124	S.D. dependent var	0.077235
S.E. of regression	0.027074	Akaike info criterion	-4.225692
Sum squared resid	0.021257	Schwarz criterion	-3.959061
Log likelihood	79.94961	Hannan-Quinn criter.	-4.133651
F-statistic	49.54043	Durbin-Watson stat	0.842177
Prob(F-statistic)	0.000000		

Table 18: PCE Deflated Short Run KWHC Equation Results

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 20:37
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.008594	0.005641	1.523415	0.1393
DLOG(PCKWHAT)	-0.203786	0.202948	-1.004131	0.3242
DLOG(PCGAS)	0.043543	0.043829	0.993489	0.3293
DLOG(PCYCAP)	-0.383035	0.198125	-1.933294	0.0637
DLOG(HDD)	0.046983	0.042610	1.102614	0.2799
DLOG(CDD)	0.152106	0.036416	4.176960	0.0003
RT(-1)	0.053178	0.200303	0.265490	0.7926

R-squared	0.507668	Mean dependent var	0.005784
Adjusted R-squared	0.398260	S.D. dependent var	0.027394
S.E. of regression	0.021250	Akaike info criterion	-4.683695
Sum squared resid	0.012192	Schwarz criterion	-4.369444
Log likelihood	86.62281	Hannan-Quinn criter.	-4.576526
F-statistic	4.640168	Durbin-Watson stat	1.918594
Prob(F-statistic)	0.002318		

Table 19: PCE Deflated Long Run KWHC Equation: No HDD + MA(1)

Dependent Variable: LOG(KWHC)
Method: Least Squares
Date: 03/16/13   Time: 20:30
Sample: 1977 2011
Included observations: 35
Failure to improve SSR after 11 iterations
MA Backcast: 1976

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.251325	0.153357	47.28409	0.0000
LOG(PCKWHAT)	-0.602345	0.066197	-9.099310	0.0000
LOG(PCGAS)	0.127180	0.022185	5.732799	0.0000
LOG(PCYCAP)	-0.221774	0.077023	-2.879316	0.0074
LOG(CDD)	0.132950	0.016418	8.097920	0.0000
MA(1)	0.996938	0.096818	10.29707	0.0000

R-squared	0.933239	Mean dependent var	8.734473
Adjusted R-squared	0.921728	S.D. dependent var	0.077235
S.E. of regression	0.021608	Akaike info criterion	-4.676676
Sum squared resid	0.013541	Schwarz criterion	-4.410044
Log likelihood	87.84182	Hannan-Quinn criter.	-4.584635
F-statistic	81.07644	Durbin-Watson stat	2.320848
Prob(F-statistic)	0.000000		

Inverted MA Roots	-1.00

Table 20: PCE Deflated Short Run KWHC Equation: No HDD

Dependent Variable: DLOG(KWHC)
Method: Least Squares
Date: 03/16/13 Time: 20:42
Sample (adjusted): 1978 2011
Included observations: 34 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009787	0.005558	1.760928	0.0892
DLOG(PCKWHAT)	-0.094791	0.177928	-0.532749	0.5984
DLOG(PCGAS)	0.027086	0.041368	0.654773	0.5180
DLOG(PCYCAP)	-0.358340	0.197612	-1.813349	0.0805
DLOG(CDD)	0.155742	0.036406	4.277968	0.0002
RT(-1)	-0.014325	0.191452	-0.074822	0.9409

R-squared	0.485499	Mean dependent var	0.005784
Adjusted R-squared	0.393624	S.D. dependent var	0.027394
S.E. of regression	0.021332	Akaike info criterion	-4.698474
Sum squared resid	0.012741	Schwarz criterion	-4.429117
Log likelihood	85.87407	Hannan-Quinn criter.	-4.606616
F-statistic	5.284330	Durbin-Watson stat	1.791447
Prob(F-statistic)	0.001531		

Curriculum Vita

David Macias was born in El Paso, Texas. He graduated from Lawrence D. Bell High School in Bedford, Texas in 1984, and briefly attending the University of Texas at Arlington. He transferred to the University of Texas at El Paso in the fall of 1985. In 1986, he took on a full time position at a currency exchange and exporting company. In 1990, he obtained a license as a United States Customs Broker, and accepted a position as director of exports to Mexico. Following the completion of his undergraduate degree, he obtained a position at Wells Fargo Bank as a mortgage loan officer. In the fall of 2009, he began a career in the electric utility industry as a real time energy trader at El Paso Electric Company. During this time, he enrolled in the Master of Science in Economics program at the University of Texas at El Paso. He is currently employed at El Paso Electric Company in the investor relations and investment oversight department as a financial analyst.

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