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Residential Electricity Demand in El Paso

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Abstract: This study analyzes the demand for residential electricity in El Paso, Texas, USA. Annual data are provided by El Paso Electric Company covering the period from 1977 to 2014. This study reports a negative long-run income elasticity for residential electricity demand. Per customer residential electricity usage declines by 0.68 percent for every 1-percent increase in real per capita income over the long run, indicating that electricity is treated as an inferior good by households in this metropolitan economy. That result runs counter to many earlier studies but corroborates recent empirical evidence for Seattle, Washington, and other regions of the United States. Further examination of residential electricity consumption behavior is warranted. Rate policy issues are also discussed.

1. Introduction

Classical demand theory systematically includes income as a primary determinant (Barten, 1968). Most of the existing empirical literature on the residential demand for electricity reports a positive relationship between income and consumption, suggesting that electricity is a normal good (Dergiades and Tsoulfidis, 2008). However, some studies indicate that electricity is an "inferior good" with sales that are negatively correlated with incomes (Roth, 1981). That includes evidence that residential electricity may behave like an inferior good in the United States as a whole (Contreras et al., 2009). Research conducted at the regional level may shed additional light on the responsiveness of residential electricity demand to changes in income.

This study examines the residential demand for electricity with data for the low income metropolitan economy of El Paso, Texas. Most utilities do not serve native loads that encompass entire states and, therefore, are more interested in localized service regions. Another reason to study electricity demand at the metropolitan level is that different regions across nations and within individual states may exhibit considerable economic and customer base heterogeneity (Provenzano and Walasek, 1981; Cebula, 2012). Income heterogeneity may lead to biased estimators, especially in large states such as Texas where earnings disparities are quite large (Wooldridge, 2009; Ayllon, 2013).

El Paso Electric Company provides electricity service to El Paso County, Texas. The 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. El Paso Electric has a net dependable generating capability of approximately 2,010 megawatts (MWs) and a 2015 native peak demand of 1,787 MWs. New generation is already under construction to allow the company to keep pace with an estimated 2.9 percent compound annual growth rate in MW peak demand during the 2011 to 2020 forecast period (Patton, 2012).

An autoregressive distributed lag (ARDL) bounds testing approach is used to analyze El Paso residential electricity usage. This approach is relatively attractive because it allows estimating both long-term and short-term consumption relationships within a single modeling framework (Halicioglu, 2007). Another useful feature of this general approach is that its informational requirements are typically not very extensive. For many regions in the United States and elsewhere, county and municipal data are much less abundant than macroeconomic variables, making it difficult to carry out econometric analyses that require substantial statistical detail. For El Paso Electric, annual frequency data from 1977 to 2014 are available to complete the study.

A three-year out of sample forecast is used to evaluate the rates of growth in demand that can be expected given a continuation of recent historical trends in the explanatory variables. 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 almost always requires several years to complete. Failure to file far enough in advance for a new permit to build generating plant additions will force utilities to have to engage in expensive off-system power purchases. Knowledge of the demand for electricity and the accurate estimation of future demand growth have important economic and regulatory repercussions and are critical elements in the planning process for all electric companies (Dortolina and Nadira, 2005).

2. Literature review

The first econometric studies of the demand for electricity can be traced back to Houthakker (1951). Results in that study point to relatively strong sensitivity of British electricity usage to changes in price and income. Halvorsen (1975) finds that United States electricity demand is highly responsive to rate changes. Estimates of the long-run price elasticity range between -1.00 to -1.21 and are statistically significant at the 1-percent level. In another nationwide study of demand conditions in the United States, Anderson (1973) highlights the importance of increasing utilization of central heating and electrical appliances in boosting residential electricity consumption.

Some studies of residential electricity demand utilize survey data to provide insights into the effects of specific household characteristics. The short-run income elasticity of demand is examined in a survey study conducted by Branch (1993). The income coefficient is positive, and both the income and price elasticities are lower than one in absolute value. Other variables that raise household electricity usage include family size, family member ages, and the number of rooms in the home. Alberini et al. (2011) use a mixed panel multi-year cross-section of households to study electricity demand. Short-run price elasticity estimates are relatively large in magnitude, ranging from -0.67 to -0.86, while the estimated income elasticities are near zero. In another survey-based study, Archibald et al. (1982) examine seasonal variation in electricity consumption. Empirical results suggest that price elasticity is higher in absolute value during periods of peak demand and that income elasticities are positive, implying that residential electricity is a normal good.

A re-examination of residential electricity demand is undertaken by Houthakker (1980) with pooled cross-sectional and time series state level data. Substantial diversity among price and income coefficients at the regional level is documented. Owing to variations in the demand for electricity across geographic areas, several studies have focused on particular regions. Using household data from Quebec, Bernard et al. (2011) report statistically significant results that indicate that demand is highly elastic with respect to the price of electricity and moderately inelastic with respect to the prices of oil and natural gas. Interestingly, income elasticities are insignificant at the 5-percent level. In a study of five southern states in the United States, Hsing (1994) estimates residential demand for electricity using a cross-sectional and time-wise autoregressive model. Short-run elasticities for price and income are found to be -0.239 and 0.397, respectively.

While most studies on the topic report evidence that electricity is a normal good, some researchers have obtained results that challenge this notion. Wilson (1971) reports a statistically significant inverse relationship between income and household electricity usage for a sample of 77 cities in the United States. Roth (1981) employs municipal electricity consumption data for a single electric utility in the southwestern United States. Results indicate that residential electricity is treated as an inferior good. In a study covering all 50 states and the District of Columbia, Contreras et al. (2009) also finds that residential electricity is an inferior good. The study uses the average price of electricity, number of households, personal income, census region dummy variables, and weather conditions to estimate electricity demand. The results also indicate that different regions of the United States display similar demand characteristics for electricity and exhibit less heterogeneity than previous studies indicate.

The issue of whether to employ marginal or average electricity prices in econometric analysis has long been a source of debate (Roth, 1981; Alberini et al., 2011). The absence of accurate rate histories leads many researchers to use the average price of electricity in regression models (Shin, 1985). Cicchetti and Smith (1975) provide evidence that average revenue measures can be employed reliably as price variables. Even though allowances for simultaneity may be necessary, average price variables in place of marginal prices are not found to cause specification errors.

A number of studies examine whether consumers respond to marginal electricity prices, which may be difficult to discern, or to average prices. Shin (1985) argues that consumers' response to marginal price changes is complicated by imperfect information owing to the complexity of rate structures and billing statements. Empirical results indicate that consumers respond to average rates as inferred from monthly electric bills. Ito (2014) provides further evidence that consumers respond to the average price of electricity rather than marginal price. Estimation results indicate that, when marginal price and average price change in opposite directions, residential electricity usage responds to the average price. 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. The study evaluates twelve utility pilot programs that use In-Home Displays (IHDs) to give direct feedback on the price of electricity at the moment of consumption. Results indicate that energy savings range from three to thirteen percent when real-time knowledge of price is made available to the consumer, but it is unclear if consumers will use the displays to alter long-term usage patterns.

Several studies seek to identify both the short-term and long-term effects on electricity demand of various explanatory variables. Silk and Joutz (1997) use an error correction approach to model annual U.S. residential electricity demand from 1949 to 1993. Long-run parameter estimates indicate that alternative fuel sources have elasticities of less than 0.05. The small magnitude of this effect may be due to constraints on consumer ability to switch fuel sources. Long-run elasticities for price and income are found to be -0.48 and 0.52, respectively, and short-run elasticities are about one-half of those found in the long-run model. Taylor (1975) notes that long-term price and income elasticities of electricity demand are often larger than short-run elasticities. While the stock of electricity consuming capital is fixed in the short-run, it is easier to modify the demand for electricity in the long-run by adjusting household appliance stocks.

Narayan et al. (2007) employ a panel cointegration technique to estimate income and price elasticities for per capita residential electricity consumption in high-income countries. Estimated long-run elasticities of demand are 0.31 with respect to income and -1.45 with respect to price. The magnitude of the price elasticity estimate indicates that rate increases may be helpful in attaining energy conservation goals. The elasticity of the substitute good price is 1.77. In the short-run, unexpectedly, all of the estimated parameters carry negative signs, though none of these coefficients are found to be statistically significant at the 5-percent level. In a similar study, Dergiades and Tsoulfidis (2008) include the stock of occupied housing as an explanatory variable in order to proxy the stock of household appliances. A 1% increase in the per capita occupied stock of housing is found to generate a 1.5% increase in per capita electricity consumption. 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, indicating that short-run departures from the long run equilibrium will dissipate in 2.75 years. This estimate is very similar to the error correction coefficient obtained by Silk and Joutz (1997).

Recent empirical research of residential electricity consumption reports a long-run negative income elasticity for Seattle, Washington (Fullerton et al., 2012), based on an error correction model estimated using annual data for the years 1960 to 2007. Data constraints necessitated employing the average price of electricity per kilowatt hour consumed as the rate variable. Empirical results indicated that residential demand is price inelastic in the long-run and the short-run. The long-run income elasticity coefficient was negative and statistically significant at the 1-percent level. This result indicates that households treat electricity as an inferior good in Seattle. In the short-run, a positive income elasticity parameter implies that residential electricity is treated as a normal good. The error correction coefficient is found to be -0.19, suggesting that consumption shocks take approximately 5.2 years to fully dissipate.

This study investigates residential electricity usage for El Paso, Texas. The El Paso metropolitan economy differs substantially from Seattle. Seattle is a high-income economy located in a rainy, coastal, forested area where electricity consumption peaks during winter months. In contrast, El Paso is a landlocked, low-income metropolitan economy located in a hot, semi-arid desert environment where peak loads occur during summer months. Residential electricity usage in this region may differ substantially from what is observed in Seattle.

3. Data

The dependent variables in this analysis are residential electricity consumption, measured in kilowatt hours (KWH) per customer, and the number of customers billed by El Paso Electric. As previously noted, there is some debate regarding whether the price variable for electricity should be the average price, the marginal price, or both. El Paso Electric currently utilizes a single block residential rate that includes a one cent increase per KWH for summer rates compared to the winter rate. Based on recent empirical evidence that finds consumers respond to the average price (Ito, 2014), and due to a lack of detailed historical marginal rate schedules from prior years, average revenue per KWH is employed as the own-price variable. Data for revenue, electricity consumption, and the number of customers are obtained from El Paso Electric Company filings with the Federal Energy Regulatory Commission (FERC). Annual frequency data from 1977 to 2014 are utilized in the analysis.

Some regions of the United States do not offer energy sources that are viable alternatives to 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, natural gas serves as a substitute good and many households use it for multiple purposes. Accordingly, the price for residential natural gas is included in the model specification to avoid omitted variable bias (Shin, 1985; Hsing, 1994; Narayan et al., 2007; Alberini et al., 2011). Residential natural gas prices are obtained from Texas Gas Service.

It has long been recognized that climate exerts a heavy influence on residential electricity usage in many regions (Wilson, 1971). Data on heating degree days (HDD) and cooling degree days (CDD) 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. Due to the limited degrees of freedom available for this analysis, a single composite indicator of inhospitable outdoor temperatures is created by summing heating and cooling degree days (Nasr et al., 2000).

Per capita income is included to account for income effects and cyclical economic conditions that influence residential energy consumption. The personal consumption expenditures (PCE) deflator is used to express the price and income data in constant 2009 dollars. Data on per capita income for El Paso County and the PCE deflator are obtained from the U.S. Bureau of Economic Analysis (BEA). Finally, information on single- and multi-family housing stocks will be used to analyze the evolution of the customer base across time. Data on those variables are obtained from IHS Economics and Moody's Analytics. The names, definitions, and units of measure of all variables in the sample are listed in Table 1.

Table 1. Mnemonics and definitions.

Variable	Definition
C	Kilowatt Hours per Residential Customer
PE	Price per Kilowatt Hour of Electricity, Real U.S. Dollars, Base Period 2009
PG	Price per CCF of Natural Gas, Real U.S. Dollars, Base Period 2009
Y	Real per Capita Income, Thousand U.S. Dollars, Base Period 2009
DD	Sum of Heating and Cooling Degree Days
CSTM	Number of Residential Customers, Thousands
SF	Single-Family Housing Stock, Thousands
MF	Multi-Family Housing Stock, Thousands
PCE	Personal Consumption Expenditures Price Index, Base Period 2009

4. Theoretical model

The demand function utilized incorporates both economic and climatic determinants of electricity consumption (Silk and Joutz, 1997). The basic form of the long-run demand equation is shown in Equation (1). The data are transformed using natural logarithms prior to estimation. The resulting coefficients, therefore, represent elasticities of residential electricity demand.

$$\ln C_t = a_0 + a_1 \ln PE_t + a_2 \ln PG_t + a_3 \ln Y_t + a_4 \ln DD_t + u_t \quad (1)$$
$$\qquad\qquad (-) \qquad (+) \qquad (+) \qquad (+)$$

Equation (1) displays how per customer electricity consumption, *C*, evolves over time. The expected signs of the parameters are shown in the parentheses under the explanatory variables. Increases in the price per kilowatt hour, *PE*, are expected to reduce the demand for residential electricity. If electricity and natural gas are substitutes, increases in the price of gas, *PG*, should lead to an increase in electricity consumption (Alberini et al., 2011).

The positive coefficient for the per capita income variable, *Y*, implies that electricity is consumed as a normal good by El Paso households. Many, if not most, prior empirical studies indicate that increases in income lead to an increase in residential electricity usage (Espey and Espey, 2004). However, as mentioned above, two recent studies report negative income elasticities for the demand of electricity (Contreras et al., 2009; Fullerton et al., 2012). The coefficient for the composite degree days variable, *DD*, is hypothesized to be positive due to the desire for more comfortable and healthy household environments during hot and cold periods (Wilson, 1971; Taylor, 1975).

In order to determine whether the variables included in Equation (1) are cointegrated, an ARDL model is estimated and a bounds testing procedure is applied (Pesaran and Shin, 1998; Pesaran et al., 2001). This approach has been previously utilized to analyze electricity demand in various countries (Halicioglu, 2007; Dergiades and Tsoulfidis, 2008; Adom et al., 2012) and has also been used to model natural gas demand at a regional level (Payne et al., 2011). One advantage of the bounds testing approach is that it does not require that all of the potentially cointegrated variables be I(1), but rather allows for cases in which the variables are I(0), I(1), or a mix of the two. Another advantage of this approach to cointegration testing is that its small sample properties are relatively favorable (Narayan, 2005). The latter is particularly important for many medium- and small-sized public utilities where data constraints often exist.

In the first step, an ARDL specification of Equation (1) is developed. The Akaike Information Criterion or Schwarz Bayesian Criterion can be used to select the optimal number of lags of each variable (Enders, 2010). A general ARDL specification is shown in Equation (2), where i is an index for lags, p is the optimal number of dependent variable lags, q_j is the optimal number of lags for each explanatory variable, and ω_t is an error term.

$$\ln C_t = \alpha_0 + \sum_{i=1}^{p} \gamma_i \ln C_{t-i} + \sum_{i=0}^{q_1} \alpha_{1i} \ln PE_{t-i} + \sum_{i=0}^{q_2} \alpha_{2i} \ln PG_{t-i} + \sum_{i=0}^{q_3} \alpha_{3i} \ln Y_{t-i} + \sum_{i=0}^{q_4} \alpha_{4i} \ln DD_{t-i} + \omega_t \quad (2)$$

The long-run coefficients are calculated using the estimated a_{ji} parameters as shown in Equation (3), where j is an index identifying the explanatory variables considered in this model. The long-run coefficients are then substituted into Equation (1), which can be rearranged to calculate the residuals, u_t, that will be included in the short-run error correction equation if a cointegrating relationship is found to exist.

$$a_j = \sum_{i=0}^{q_j} \alpha_{ji} / (1 - \sum_{i=1}^{p} \gamma_i) \quad (3)$$

In order to test whether the variables in Equation (1) are indeed cointegrated, a bounds test is then conducted (Pesaran et al., 2001). To this end, Equation (4) is estimated, where Δ is the first-difference operator and v is a random error term.

$$\Delta \ln C_t = b_0 + \sum_{i=1}^{p-1} d_i \Delta \ln C_{t-i} + \sum_{i=0}^{q_1-1} b_{1i} \Delta \ln PE_{t-i} + \sum_{i=0}^{q_2-1} b_{2i} \Delta \ln PG_{t-i} + \sum_{i=0}^{q_3-1} b_{3i} \Delta \ln Y_{t-i} + \sum_{i=0}^{q_4-1} b_{4i} \Delta \ln DD_{t-i} + b_5 \ln C_{t-1} + b_6 \ln PE_{t-1} + b_7 \ln PG_{t-1} + b_8 \ln Y_{t-1} + b_9 \ln DD_{t-1} + v_t \quad (4)$$

The null hypothesis of no cointegration can be evaluated by calculating the *F*-statistic for H_0: $b_5 = b_6 = b_7 = b_8 = b_9 = 0$. Pesaran et al. (2001) present one set of critical values for the case where all variables are I(0) and another set of critical values is computed for the I(1) case. When the calculated *F*-statistic falls between the upper and lower critical values, results of the test are indeterminate. When the *F*-statistic is larger than the upper bound, the null hypothesis can be rejected. Narayan (2005) presents bounds test critical values for sample sizes ranging from 30 to 80 observations. The latter critical values are used in the empirical analysis below.

In the final step, the short-run error correction equation is estimated. Short-run departures from the long-run equilibrium can be precipitated by a variety of factors. When those shocks occur, consumption is hypothesized to respond in a manner that allows the equilibrium to eventually be re-attained. The specification for the short-run usage equation is shown in Equation (5).

$$\Delta \ln C_t = \beta_0 + \sum_{i=1}^{p-1} \delta_i \Delta \ln C_{t-i} + \sum_{i=0}^{q_1-1} \beta_{1i} \Delta \ln PE_{t-i} + \sum_{i=0}^{q_2-1} \beta_{2i} \Delta \ln PG_{t-i} + \sum_{i=0}^{q_3-1} \beta_{3i} \Delta \ln Y_{t-i} + \sum_{i=0}^{q_4-1} \beta_{4i} \Delta \ln DD_{t-i} + \varphi u_{t-1} + \varepsilon_t \quad (5)$$

The residuals from Equation (1), calculated using the long-run coefficients from Equation (3), are lagged and included in the short run equation as the error correction term, u_{t-1}. The coefficient for the error correction term, which indicates the rate at which a short-run departure from equilibrium will dissipate, is expected to be negative. The time required for complete adjustment to the long-run equilibrium increases as the value of the error correction coefficient approaches zero.

Growth in a utility customer base also affects peak load demand. Careful analysis of customer base growth is required to ensure sufficient generating capacity is available to service native load and reserve requirements. Accordingly, a model is developed for variations in the number of residential customers. The basic form of the long-run equation for the residential customer base is specified in Equation (6).

$$\ln CSTM_t = c_0 + \underset{(+)}{c_1 \ln SF_t} + \underset{(+)}{c_2 \ln MF_t} + \underset{(+)}{c_3 \ln Y_t} + w_t \quad (6)$$

In Equation (6), the single-family housing stock (SF) and the multi-family housing stock (MF) are hypothesized to be positively correlated with growth in the customer base. The number of residential customers is also expected to fluctuate in tandem with prevailing regional economic conditions. The latter are approximated by El Paso County real per capita income (*Y*). To investigate short- and long-run customer base dynamics, an ARDL model will be estimated following the same steps outlined above in the case of per-customer electricity consumption. The lagged residuals from the long-run customer account model, w_{t-1}, will be included in the short-run equation if a cointegrating relationship is uncovered.

Finally, it is important to test whether the parameters of the estimated models are stable or change significantly over time. To evaluate parameter stability, the cumulative sum (CUSUM) and cumulative sum of squares (CUMUMSQ) tests are conducted (Brown et al., 1975). If the statistics remain within the 5-percent critical bounds, it is not possible to reject the null hypothesis that the parameters are stable across time.

5. Empirical results

The ARDL approach utilized is not appropriate for variables that are integrated of an order greater than one (Pesaran et al., 2001). Phillips-Perron unit root tests indicate that all the variables included in the two models are either I(0) or I(1). Thus, the data are suitable for analysis within the ARDL framework. The Akaike Information Criterion is utilized for lag-length selection in developing the ARDL models for electricity consumption and customers. A maximum of three lags of each variable are considered for inclusion in the models due to degree of freedom constraints.

An ARDL(2,1,3,2,0) model is selected for per customer electricity consumption. Diagnostic statistics for the model are presented in Table 2 along with estimated long-run elasticities. A Ljung-Box *Q*-statistic for the null hypothesis that the residuals are not autocorrelated, calculated using a residual autocorrelation function for lags of up to four years, indicates that serial correlation is not problematic. The calculated *F*-statistic for H_0: $b_5 = b_6 = b_7 = b_8 = b_9 = 0$ is 6.42. This is higher than the 5-percent critical value for the upper bound computed by Narayan (2005). This indicates that the variables included in the model are cointegrated. As additional diagnostic checks, the CUSUM and CUSUMSQ tests of parameter stability are carried out. Figures 1 and 2 show that the model's parameters are relatively stable over time and the calculated statistics do not surpass the 5-percent critical bounds.

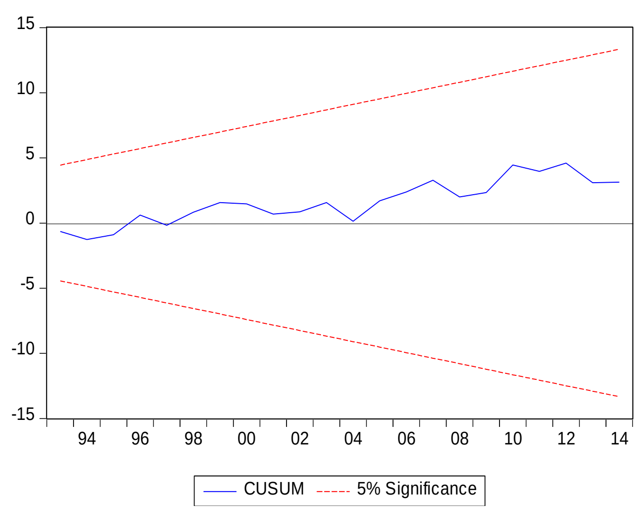

Figure 1. CUSUM results for electricity consumption per customer.

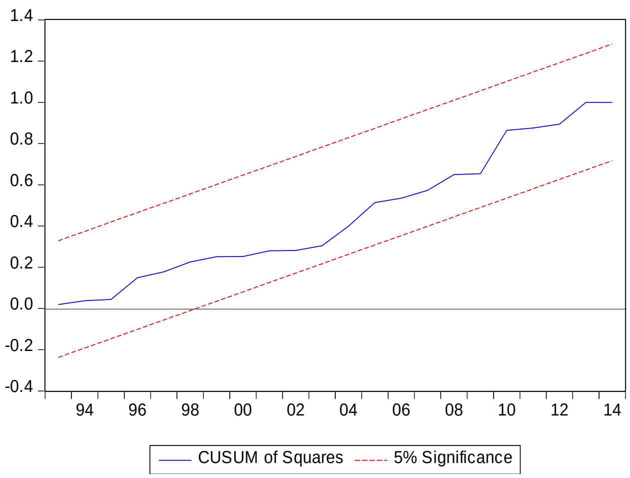

Figure 2. CUSUMSQ results for electricity consumption per customer.

All of the long-run coefficient estimates in Table 2 are significant at the 5-percent level. Furthermore, with the exception of the parameter estimate for per capita income, all of the estimated coefficients exhibit the hypothesized signs. The own-price elasticity of -1.25 is larger in magnitude than the mean long-run price elasticity of -0.85 reported by Espey and Espey (2004) in a survey of prior research. It suggests that El Paso consumers are highly responsive to variations in the real price of electricity in the long-run. That is plausible. Other studies have also obtained long-run own-price elasticities that are greater than 1.0 in absolute value (Narayan et al., 2007; Dergiades and Tsoulfidis, 2008; Bernard et al., 2011).

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 long-run elasticity of demand with respect to the price of natural gas is 0.28, indicating that natural gas is an imperfect substitute good for electricity in El Paso. This parameter falls within the range of cross price elasticities, 0.04 to 0.32, reported in earlier studies (Roth, 1981; Hsing, 1994; Silk and Joutz, 1997). The inelastic response to gas price variations reported here 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.

Table 2. ARDL analysis of electricity consumption per customer.

Long-run coefficients for ARDL(2,1,3,2,0) model:

Variable	Coefficient	Standard error	*t*-statistic	*p*-value
ln(*PE*)	-1.24615	0.32231	-3.8663	0.0008
ln(*PG*)	0.28271	0.07768	3.6393	0.0014
ln(*Y*)	-0.67925	0.29049	-2.3382	0.0289
ln(*DD*)	0.82952	0.22671	3.6590	0.0014

Diagnostic statistics for the underlying ARDL model:

R^2	0.9912	Akaike Information Criterion	-5.9503
Adjusted R^2	0.9865	Schwarz Bayesian Criterion	-5.3726
F-statistic	207.56	Probability (*F*-statistic)	0.000000
Ljung-Box *Q*-statistic	4.9209	Probability (*Q*-statistic)	0.296

Bounds test results:		Bounds test 5-percent critical values	
F-statistic	6.4196	Lower bound I(0)	3.276
		Upper bound I(1)	4.630

Note: Bounds test critical values are from Narayan (2005).

The negative parameter estimate for per capita income indicates that residential electricity in El Paso County is treated as an inferior good. That result runs contrary to the majority of earlier studies of residential electricity demand (Wilder et al., 1990). However, it may have a plausible explanation. As incomes rise, consumers may upgrade household appliance stocks, leading to reductions in electricity consumption because newer appliances and housing structures tend to be more energy efficient (Schipper and Ketoff, 1985; Alberini et al., 2011). The parameter estimate indicates that a 1% increase in real per capita income is associated with a 0.68% decrease in residential electricity usage in the long run. This result corroborates a subset of other studies in which negative income elasticities have also been reported (Roth, 1981; Contreras et al., 2009).

As hypothesized, the explanatory variable for aggregate cooling and heating degree days (*DD*) is positively correlated with residential electricity usage. This suggests that household cooling is an important end use of electric energy in El Paso. It also suggests that customers probably spend more time indoors during inclement weather. Nasr et al. (2000) document higher electricity consumption during periods of hot or cold weather. In El Paso, a 1% increase in annual heating and cooling degree days increases residential electricity consumption by approximately 0.83%.

Estimation results for the short-run error correction equation are summarized in Table 3. The short-run own-price elasticity of -0.24 is substantially smaller in terms of absolute value than the long-run elasticity shown in Table 2. Other studies have also found that short-run price elasticities are smaller in magnitude than corresponding long-run elasticities (Narayan et al., 2007; Dergiades and Tsoulfidis, 2008; Bernard et al., 2011; Fullerton et al., 2012). This makes intuitive sense. In the short-run, consumers tend to respond to price increases by reducing usage of existing electrical devices. In the long-run, greater reductions in consumption can be achieved by the acquisition of new energy-saving appliances.

The contemporaneous short-run cross-price elasticity for natural gas is positive, as hypothesized, but the coefficient does not satisfy the 5-percent significance criterion. Contrary to expectations, the coefficients on one- and two-year lags of the gas price variable are negative and statistically significant. Garcia-Cerruti (2000) obtains similar results, indicating that consumers sometimes treat natural gas and electricity as complements. It is plausible that higher prices for fuels such as natural gas may encourage adoption of devices that are more energy-efficient overall, thus reducing residential electricity consumption after a lag of one or two years. Another possibility is that lagged natural gas prices proxy for electricity prices since natural gas is a major input to electricity generation in El Paso and the price of fuel inputs is an important determinant of retail electricity prices (Girish and Vijayalakshmi, 2013; EPEC, 2016).

Table 3. Electricity consumption per customer error correction results.

Dependent variable: $\Delta\ln(C_t)$

Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Constant	0.455507	0.048343	9.4223	0.0000
$\Delta\ln(C_{t-1})$	-0.384332	0.089158	-4.3107	0.0002
$\Delta\ln(PE_t)$	-0.243728	0.040067	-6.0830	0.0000
$\Delta\ln(PG_t)$	0.000413	0.005143	0.0804	0.9366
$\Delta\ln(PG_{t-1})$	-0.078786	0.013549	-5.8150	0.0000
$\Delta\ln(PG_{t-2})$	-0.038415	0.012579	-3.0540	0.0053
$\Delta\ln(Y_t)$	0.472135	0.132157	3.5725	0.0015
$\Delta\ln(Y_{t-1})$	0.187731	0.112534	1.6682	0.1078
$\Delta\ln(DD_t)$	0.222865	0.028668	7.7741	0.0000
u_{t-1}	-0.290013	0.031283	-9.2705	0.0000

Diagnostic statistics:

R^2	0.8801	Akaike Information Criterion	-6.1312
Adjusted R^2	0.8369	Schwarz Bayesian Criterion	-5.6869
F-statistic	20.390	Probability (*F*-statistic)	0.00000
Ljung-Box *Q*-statistic	5.1761	Probability (*Q*-statistic)	0.270

The impact of real per-capita income is positive both contemporaneously and after a one-year lag, although the latter effect does not satisfy the standard significance criterion. Thus, the hypothesis regarding the direct effect of income on residential electricity sales is upheld in the short-run. The results for El Paso are similar to those reported in Fullerton et al. (2012) for Seattle with a short-run income elasticity that is positive, but a long-run elasticity coefficient that is negative. The outcomes suggest that household electricity usage is directly correlated with the business cycle in the short run. Electric-energy-saving effects of higher incomes appear to be manifested over the long run as older, less efficient electrical devices are gradually upgraded. Finally, extreme temperatures, as represented by total cooling and heating degree days, have strong immediate impacts on residential electricity demand.

As hypothesized, the sign for the error correction parameter (u_{t-1}) is less than zero. The value of the error correction coefficient is -0.29, indicating that approximately 29% of the consumption deviation from the long-run equilibrium dissipates within one year. A total of approximately 3.4 years are required for a long-run equilibrium to be fully regained, a somewhat longer amount of time for this border metropolitan economy than the sub-three year periods reported in some residential studies using national KWH data (Silk and Joutz, 1997; Dergiades and Tsoulfidis, 2008).

For investor-owned utilities like El Paso Electric, anticipating growth in the customer base is important in order to successfully maintain sufficient generation, transmission, and distribution capacity. Capital expansion projects for those facilities must be planned in advance (Shockley and Heitz, 2012). Rights of way for transmission poles and substations entail lengthy regulatory and environmental permitting requirements. Understanding residential customer growth is part of the planning process and requires models that incorporate both demographic and economic factors. The long-run customer base specification shown in Equation (6) above incorporates both factors. Estimation results are shown in Table 4.

Table 4. ARDL analysis of the customer base.

Long-run coefficients for ARDL(3,0,3,3) model:

Variable	Coefficient	Standard error	*t*-statistic	*p*-value
ln(*SF*)	0.79575	0.11185	7.1143	0.0000
ln(*MF*)	0.33328	0.03727	8.94193	0.0000
ln(*Y*)	0.02291	0.10381	0.2207	0.8274

Diagnostic statistics for the underlying ARDL model:

R^2	0.9997	Akaike Information Criterion	-7.6362
Adjusted R^2	0.9996	Schwarz Bayesian Criterion	-7.0585
F-statistic	6531.68	Probability (*F*-statistic)	0.00000
Ljung-Box *Q*-statistic	5.949	Probability (*Q*-statistic)	0.203

Bounds test results:		Bounds test 5-percent critical values	
F-statistic	5.746	Lower bound I(0)	3.276
		Upper bound I(1)	4.630

Note: Bounds test critical values are from Narayan (2005).

An ARDL(3,0,3,3) model is selected on the basis of the Akaike Information Criterion. The *Q*-statistic indicates that the null hypothesis of no residual autocorrelation cannot be rejected. The *F*-statistic calculated for the bounds test is 5.75, which exceeds the 5-percent critical value for the upper bound, indicating that a cointegrating relationship has been found for the residential customer base. Finally, CUSUM and CUSUMSQ results are shown in Figures 3 and 4. The computed statistics remain within the 5-percent critical bounds, indicating the absence of significant deviations from the null hypothesis of parameter stability.

As expected, all three independent variables are directly correlated with customer growth. The long-run coefficients indicate that a 1% increase in the single-family housing stock leads to a 0.80% increase in the residential customer base, while a 1% increase in the stock of multi-family housing leads to a 0.33% increase in the number of residential accounts. After accounting for the impact of the housing stock on the number of customer accounts, per-capita income has a positive, but statistically insignificant, effect. The housing stock appears to be the main driver of residential account growth in El Paso over the long run, but the increases in the customer base due to income gains are not very reliable.

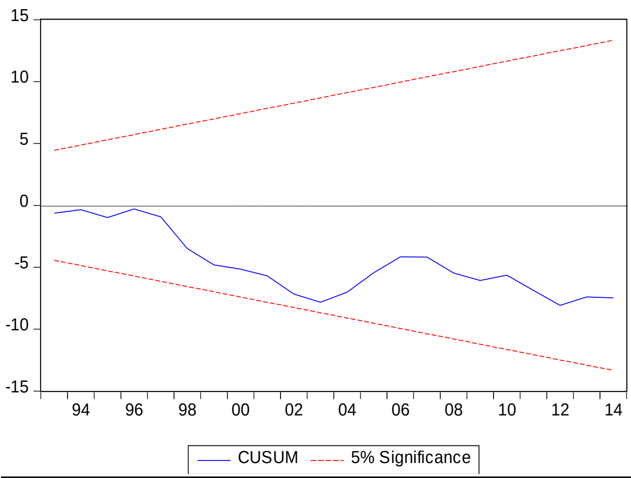

Figure 3. CUSUM results for the customer base.

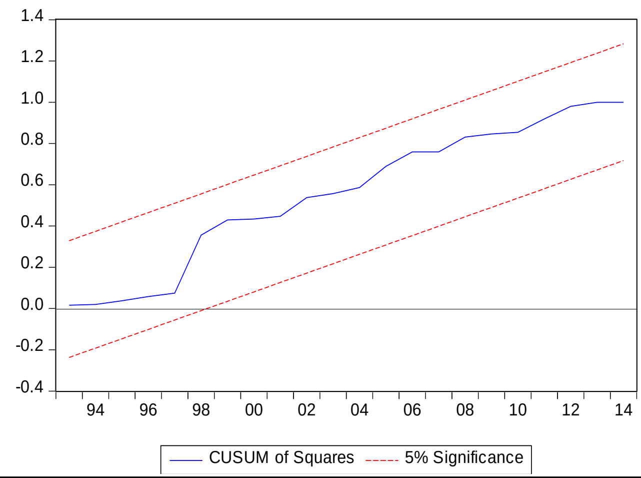

Figure 4. CUSUMSQ results for the customer base.

Results for the short-run error correction equation for residential customer growth are shown in Table 5. The estimated coefficient for the single-family housing stock is positive and statistically significant. The multi-family housing stock has a positive and significant impact on customer accounts within one year, although minor reversals occur on a statistically insignificant basis over the course of the subsequent two years. The parameter magnitudes in these results suggest that shifts in the housing stock translate fairly quickly into changes in the number of residential electrical accounts.

Table 5. Customer base error correction results.

Dependent variable: $\Delta\ln(CSTM_t)$

Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Constant	-0.091807	0.021254	-4.3195	0.0002
$\Delta\ln(CSTM_{t-1})$	-0.166464	0.090158	-1.8464	0.0772
$\Delta\ln(CSTM_{t-2})$	-0.152010	0.099168	-1.5329	0.1384
$\Delta\ln(SF_t)$	0.634005	0.160178	3.9581	0.0006
$\Delta\ln(MF_t)$	0.688987	0.073089	9.4267	0.0000
$\Delta\ln(MF_{t-1})$	-0.134236	0.124020	-1.0824	0.2898
$\Delta\ln(MF_{t-2})$	-0.126612	0.090049	-1.4060	0.1725
$\Delta\ln(Y_t)$	-0.020183	0.049186	-0.4103	0.6852
$\Delta\ln(Y_{t-1})$	-0.052437	0.044308	-1.1835	0.2482
$\Delta\ln(Y_{t-2})$	0.081694	0.041317	1.9773	0.0596
w_{t-1}	-0.770023	0.154062	-4.9981	0.0000

Diagnostic statistics

R^2	0.8700	Akaike Information Criterion	-7.7509
Adjusted R^2	0.8158	Schwarz Bayesian Criterion	-7.2621
F-statistic	16.057	Probability (*F*-statistic)	0.00000
Ljung-Box *Q*-statistic	6.186	Probability (*Q*-statistic)	0.186

Changes in per-capita income do not translate into greater, or fewer, customer accounts very quickly. That is probably due to leasing contracts, security deposit requirements, housing down payment accumulation, mortgage application procedures, school enrollments, and other institutional factors that affect the rate of household formation. Following a two-year lag, however, per-capita income is found to generate changes in the number of residential electricity customers, but not with enough regularity to satisfy the standard significance criterion. The parameter estimate for per capita income indicates that the local business cycle has a small positive effect on the number of electricity accounts, even after accounting for variations in the housing stock. This effect suggests that economic slowdowns delay the occupancy of new housing units and increase the amount of time that existing homes remain vacant.

The error correction term is negative and less than one, as hypothesized. The magnitude of the error correction term indicates that approximately 77% of the adjustment toward long-run equilibrium occurs in the first year following a deviation from it. Only 1.3 years is required to fully dissipate a deviation from the long-run equilibrium. That is substantially faster than what Fullerton et al. (2012) document for Seattle and points to potentially interesting customer base dynamics differing across metropolitan economies and service areas. This topic has not received very much attention in the public utility literature and may be worthwhile to investigate further.

Management decisions regarding increases to generation, transmission, and distribution capacity require demand forecasts for all rate categories, including residential. As an additional step towards examining the empirical results reported in this study, a 3-period out-of-sample simulation is conducted for residential KWH consumption and customer growth. Compound annual growth rates (CAGR) are calculated from observed historical data for El Paso Electric for the 2004 to 2014 period. The CAGRs and the 3-year forecasted values for the explanatory variables are shown in Table 6. The electricity price variable, *PE*, declined at an average rate of 1.38% per year and the real price of natural gas fell by 2.35% per year from 2004 to 2014. Real per capita income in El Paso has a CAGR of 1.54% during the decade selected, while the growth rates for the single- and multi-family housing stocks are 1.70% and 1.19%, respectively. The weather variable forecast is calculated by using a 10-year historical mean value of 4,850 for *DD*.

Table 6. Explanatory variable growth for simulation.

	PE	*PG*	*Y*	*DD*	*SF*	*MF*
10-YR CAGR	**-1.38**	**-2.35**	**1.54**	**0.00**	**1.70**	**1.19**
Year 1	0.1054	0.4819	29.61	4,850	202.8	73.94
Year 2	0.1039	0.4705	30.06	4,850	206.2	74.82
Year 3	0.1025	0.4595	30.53	4,850	209.7	75.71

Table 7 reports the forecasts for the dependent variables on the basis of the growth rates calculated for the regressors. The simulation indicates that per customer residential sales will grow from 7,392 KWH in Year 1 to 7,528 KWH in Year 3. Much of that increase is due to the 1.38% annual real price declines employed in the simulation. By the third year of the simulation, the declining price of electricity is the main driver of projected increases in electricity consumption. The results in Table 7 imply that total residential gigawatt hour (GWH) sales will increase at a compound annual growth rate of 2.89% under the conditions outlined in Table 6. The observed historical 10-year compound annual growth rate for El Paso residential sales is approximately 3.07%. The simulation properties of the estimated model seem plausible.

Table 7. Residential consumption and customer forecasts.

YEAR	***C***	**% Δ**	***GWH***	**% Δ**	***CSTM***	**% Δ**
Year 1	7,392	0.35	2,013	1.65	272.38	1.29
Year 2	7,452	0.81	2,074	3.01	278.34	2.19
Year 3	7,528	1.02	2,132	2.77	283.16	1.73

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 to improve in energy efficiency by investing in items such as multi-pane windows and better insulation. As shown in Table 2, the long-run elasticity of per customer residential electricity consumption with respect to price is -1.25. 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 well documented (Anderson, 1973; Narayan et al., 2007; Reiss and White, 2008).

On that basis, prospects for electricity conservation in El Paso are not very promising. The average El Paso Electric residential real price for electricity has failed to keep pace with inflation for three consecutive decades. By 2014, the last year in the sample period, the residential real price per kilowatt hour was 46.9 percent below its level in 1983. Although numerous factors have influenced the evolution of electricity rates in El Paso, if the long-run trend towards lower real prices for electricity continues per customer residential electricity usage is likely to continue to increase in the Texas portion of the service area.

Under normal circumstances, regulating residential energy usage through pricing policies could provide an effective tool for policymakers. However, the potential for encouraging more efficient energy use via price increases is not as straightforward as it appears. In 2011, the El Paso City Council requested rate relief from El Paso Electric, arguing that rates were too high relative to other regions (Schladen, 2011). Somewhat surprisingly, this request occurred in the midst of a 5-year, $1 billion series of capital expansion projects by El Paso Electric (Shockley and Heitz, 2012). Proponents of lower rates claim that the local economy will be more competitive as a consequence of the price reductions, but public controversy over rates neutralizes an effective tool for increased usage efficiency. In the absence of sustained rate increases that outpace inflation, aggregate residential electricity consumption in El Paso is likely to remain higher than it would be otherwise, even if real per capita incomes continue to increase in this urban economy.

One question that logically arises is whether the results obtained, particularly for the long-run income coefficient, are merely an accident of geography. Evidence reported for electricity usage in the immediately adjacent metropolitan economy of Ciudad Juárez, Mexico, indicates that is not the case (Fullerton et al., 2014). Electricity is found to behave as a normal good in that urban economy located just across a river bed that generally contains little, if any, water. Whether that is also the case for the Las Cruces, New Mexico, metropolitan economy portion of the El Paso Electric service area remains to be seen.

6. Conclusion

The long-run income elasticity reported in this study is -0.68, indicating that household electricity usage behaves as an inferior good in El Paso County. The negative income elasticity result is at odds with much of the existing literature on this topic, but it confirms similar results reported in two recent studies that employ very different data samples. This should encourage additional research at the regional level. Electricity, of course, is not a classical example of an "inferior" good, but residential electricity consumption in El Paso and other regions within the United States seems to behave as such over the long run. One possible explanation for a decline in usage as incomes rise is the adoption of energy efficiency upgrades to appliances and housing structures in recent years. Reductions in residential electricity demand per customer as per capita income increases should place less pressure on existing generation capacity, even as the regional economy continues to expand. Transmission and distribution grid growth will not, however, be lower as a consequence of this type of usage evolution.

Out of sample simulations indicate that El Paso residential electricity consumption will grow at a compound annual rate of 2.89 percent over the course of the three year forecast period if the explanatory variables continue to change at rates observed over the last decade. These results compare well to the historical growth rate for aggregate residential demand in the El Paso Electric service territory. Simulation results also indicate that per capita electricity consumption is expected to increase, driven largely by declines in the real price of electricity that offset the reductions in usage that occur as real incomes increase.

In response to steady growth in the customer account base and total sales, El Paso Electric 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 fact, the opposite may occur if the El Paso City Council enacts punitive rates against rooftop solar electricity generation. If the latter approach is implemented, it will be in stark contrast to the rate policies being designed in other desert region urban economies and may lead to unexpected outcomes.

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