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# Residential Electricity Consumption in Las Cruces, New Mexico, USA

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**Abstract**

This study examines how residential electricity consumption (KWHC) reacts to changes in the price of electricity, the price of natural gas, real income per capita, heating degree days, and cooling degree days. Annual frequency data analyzed are for Las Cruces, the second largest metropolitan economy in New Mexico. The sample period is 1977 to 2016. An Autoregressive-Distributed Lag model (ARDL) is employed to obtain long-run and short-run elasticities. In the long-run, residential consumption does not respond in a statistically reliable manner to any of the explanatory variables. All of the coefficient signs are as expected and those for real per capita income and total degree days appear plausible. In the short-run, residential consumption responds reliably to variations in all of the variables except per capita income. Somewhat surprisingly, the short-run results also include an own-price elasticity that is close to zero, implying that residential electricity has a horizontal demand curve in Las Cruces.

**Keywords:** residential electricity consumption, regional economics, business cycles

**JEL Categories**

Q41, Energy Demand; R15, Regional Econometrics; M21, Business Economics

## 1. Introduction

Recent empirical studies have attempted to model residential electricity consumption in different service areas. Such studies use data from different metropolitan economies to analyze regional residential electricity consumption behavior. Further research for different regions in the United States can help provide a better picture on how changes in income and other variables affect residential electricity sales. Beyond that, different regions may exhibit consumption patterns that differ from those that have been documented for other metropolitan economies or national economies.

In this study, residential electricity sales are examined for the Las Cruces, New Mexico metropolitan economy. Las Cruces is part of Dona Ana County with a population of 219,970 and an estimated nominal per capita income of $37,736 (Fullerton and Fullerton, 2019). Although geographically adjacent to El Paso, Texas, a nearby urban economy where residential electricity consumption has been analyzed (Fullerton et al, 2016), such an effort has not previously been completed for Las Cruces. Because it is the second largest metropolitan economy in New Mexico, this omission is somewhat surprising.

Electricity services are provided to Las Cruces by El Paso Electric Company (EPEC). EPEC is a regional electric utility that provides electricity to 400,000 retail and wholesale customers within a 10,000 square mile area. The EPEC service territory ranges from Hatch, New Mexico to Van Horn, Texas. It has a peak generating capacity of 2,010 MW (EPEC, 2016).

To examine Las Cruces residential electricity consumption, an autoregressive distributed lag (ARDL) modeling approach is utilized. The ARDL approach allows analyzing both long-run and short-run consumption relationships. EPEC annual data from 1977-2016 for the Las Cruces service area are employed for the analysis.

Subsequent sections of the study are as follows. A brief summary of related literature is provided next. An overview of the theoretical model and methodology is included in the third section. Empirical results and policy implications are then reviewed. Principal outcomes are encapsulated in the final section.

## 2. Literature Review

Early studies analyze residential electricity consumption by estimating the elasticities of residential electricity demand using variables such as price, income, and heating and cooling degree-days. Cooling and heating degree-days are usually calculated using the difference between average temperatures and a base of 65 degrees Fahrenheit. Using structural demand and price equations, Halvorsen (1975) finds that the own price elasticity of demand ranges from -1.0 to -1.21, suggesting unity in the long run.

A recurring question is whether electricity demand functions should employ marginal prices or average prices. Taylor (1975) finds that both average and marginal price should be included in demand equations in order to accurately model residential electricity. That can be problematic because data constraints for marginal electricity prices may cause average prices to be the best information available (Halvorsen, 1975). Additional research uses Ramsey specification error tests to determine that average revenue price is an adequate measure to determine residential electricity demand (Cicchetti and Smith, 1975). Wilder and Willenborg (1975) provide evidence that consumers react to monthly bills and do not fully know the marginal price of electricity, thus making average price variables appropriate to use. Results in other studies also indicate that consumers respond to the average prices implied by monthly electricity bills (Shin, 1985; Ito, 2014).

Prior research also examines the effects of income and other variables on household electricity usage (Hultman and Ramsey, 1977). Results indicate that electricity price, the price of natural gas, and income are some of the biggest determinants of residential demand for electricity. Many studies report income elasticities with positive coefficients (Wilder and Willenborg, 1975), but some do not. In a metropolitan study that includes both average and marginal price variables, Roth (1981) obtains results that imply that decreases in real incomes increase electricity demand suggesting that electricity is an "inferior good". A separate study using national data also documents similar evidence (Contreras et al, 2009). Results in that effort further indicate that weather influences on electricity are asymmetric.

A number of empirical studies simultaneously estimate long-run and short-run elasticities. Chang (1991) employs a generalized functional form method to estimate time-varying elasticities. Coefficient estimates are statistically significant and exhibit the hypothesized signs. Silk and Joutz (1997) use co-integration techniques to construct an error correction model for U.S. residential electricity demand. A subsequent U.S. study uses an autoregressive distributed lag (ARDL) approach. The ARDL cointegration technique is appropriate and attractive for models with variables of mixed order of integration (Dergiades and Tsolfides, 2008). Findings from that ARDL approach report long-run and short-run elasticities that are similar in magnitude to those reported in prior studies.

Epsey and Epsey (2004) conduct a meta-analysis of previous studies to identify factors that may affect estimated elasticities. Evidence gathered indicates that there are subtle differences among elasticities and it cannot be assumed that every region will have similar estimates. Further empirical efforts for residential electricity demand in different countries also uses results to indicate regional policy implications based on specific demand characteristics (Halicioglu, 2007; Hondroyiannis, 2004; Narayan and Smyth, 2005).

One recent effort on U.S. residential electricity demand focuses on price and income elasticities as important elements for designing regional policies (Alberini et. al., 2011). Results include a high own-price elasticity of demand and low-income elasticity. Such findings suggest that price increases will cause households to choose less energy-intensive appliances. The low-income elasticity also suggests that households will tend to invest in less energy-intensive appliances.

Recent regional studies also employ out-of-sample model simulations as additional means for confirming model reliability. One study for Seattle reports a negative long-run income elasticity (Fullerton et. al., 2012). A three-year forecast is used to help evaluate the estimated model. A similar study for residential electricity demand in Iran reports temperature as the biggest determinant of electricity demand (Pourazarm and Cooray, 2013). It includes a sevenyear dynamic forecast. Kindred research on residential electricity demand in El Paso uses an ARDL approach (Fullerton et al, 2016). The long-run income elasticity coefficient is negative and a three-year out of sample forecast is conducted to evaluate expected demand growth.

In this effort, residential electricity consumption is examined for Las Cruces, New Mexico. Las Cruces is only forty miles from El Paso, but has a different economic base and somewhat different weather patterns (Fullerton and Fullerton, 2019). There is no guarantee, therefore, that residential electricity consumption patterns in this smaller metropolitan economy will match what has been documented for the larger, nearby urban economy.

## 3. Theoretical Framework

A demand function for Las Cruces residential electricity consumption is specified using economic and weather variables. Because non-zero amount data are utilized, the variables are transformed using natural logarithms prior to estimation (Gelman and Hill, 2006). Expected coefficient signs are listed below Equation (1).

$$\ln KWHC_t = a_0 + a_1 \ln PE_t + a_2 \ln PNG_t + a_3 \ln YCAP_t + a_4 \ln HDD_t + a_5 \ln CDD_t + u_t$$

$$\qquad\qquad (-) \qquad\quad (+) \qquad\qquad (+) \qquad\qquad (+) \qquad\qquad (+) \qquad (1)$$

An autoregressive distributed lag model (ARDL) estimation approach is employed similar to that utilized for the nearby El Paso portion of the EPE service area (Fullerton et. al, 2016). The ARDL model employs a bounds testing procedure that allows for cointegration regardless of whether the variables have I(0) or I(1) orders of integration (Dergiades and Tsoulfidis, 2008). The null hypothesis of no cointegration is rejected using an F-test. More specifically, the computed F-statistic exceeds the upper bound of the test (Pesaran et. al, 2001).

Equation (2) shows the general ARDL specification (Pesaran et. al, 2001). In Equation (2), q represents the optimal number of dependent variable lags and $p_i$ is used for the optimal number of lags for each explanatory variable. The error term is represented by v with t as the time subscript.

$$\ln KWHC_t = \alpha_0 + \sum_{i=0}^{q} \gamma_i \ln KWHC_{t-i} + \sum_{i=0}^{p_1} \alpha_{1i} \ln PE_{t-i} + \sum_{i=0}^{p2} \alpha_{2i} \ln PNG_{t-i} + \sum_{i=0}^{p3} \alpha_{3i} \ln YCAP_{t-i}$$
$$+ \sum_{i=0}^{p_4} \alpha_{4i} \ln HDD_{t-i} + \sum_{i=0}^{p_5} \alpha_{5i} \ln CDD_{t-1} + v_t \qquad (2)$$

Equation (3) shows how the long-run coefficients for Equation (2) are calculated from the parameters in Equation (3). In Equation (4), j represents an index for the independent variables. The long-run coefficients are later used to calculate the residuals that will be part of the short-run error correction model if cointegration is present.

$$a_j = \sum_{i=0}^{p_j} \alpha_{ji} / (1 - \sum_{i=1}^{q} \gamma_i) \qquad (3)$$

The variables in Equation (2) are tested for cointegration by employing a bounds test (Pesaran et al, 2001). In Equation (4), $\Delta$ is a first-difference operator and w is stochastic error term. Narayan (2005) presents a set of bounds test critical values that are used for both I(0) and I(1) cases when samples contain between 30 and 80 observations. The calculated F-statistic must be larger than the upper bound to reject the null hypothesis of no cointegration $H_o = b_6 = b_7 = b_8 = b_9 = b_{10} = b_{11} = 0$. When the F-statistic is between the upper and lower bounds, the test is inconclusive. An F-statistic below the lower bound will fail to reject the null hypothesis.

$$\Delta \ln KWHC_t = b_0 + \sum_{i=0}^{q-1} d_i \Delta \ln KWHC_{t-i} + \sum_{i=0}^{p_1-1} b_{1i} \Delta \ln PE_{t-i} + \sum_{i=0}^{p2-1} b_{2i} \Delta \ln PNG_{t-i} + \sum_{i=0}^{p3-1} b_{3i} \Delta \ln YCAP_{t-i} + \sum_{i=0}^{p_4-1} b_{4i} \Delta \ln HDD_{t-i} + \sum_{i=0}^{p_5-1} b_{5i} \Delta \ln CDD_{t-i} + b_6 \ln KWHC_{t-1} + b_7 \ln PE_{t-1} + b_8 \ln PNG_{t-1} + b_9 \ln YCAP_{t-1} + b_{10} \ln HDD_{t-1} + b_{11} \ln CDD_{t-1} + w_t \tag{4}$$

If a cointegrating relationship exists, a short-run error correction model is estimated. The residuals from Equation (2) are lagged and $u_{t-1}$ is included as a regressor as shown in Equation (5). The resulting coefficient estimate for $\delta$ is known as an error correction term. The hypothesized coefficient sign for the error correction term is negative. When that condition is met, $\delta$ provides an estimate of the rate at which a short-run departure from the long-run equilibrium will dissipate. Equation (5) shows the specification for the short-run error correction model.

$$\Delta \ln KWHC_t = \beta_0 + \sum_{i=0}^{q-1} \partial_i \Delta \ln KWHC_{t-i} + \sum_{i=0}^{p_1-1} \beta_{1i} \Delta \ln PE_{t-i} + \sum_{i=0}^{p2-1} \beta_{2i} \Delta \ln PNG_{t-i} + \sum_{i=0}^{p3-1} \beta_{3i} \Delta \ln YCAP_{t-i} + \sum_{i=0}^{p_4-1} \beta_{4i} \Delta \ln HDD_{t-i} + \sum_{i=0}^{p_5-1} \beta_{5i} \Delta \ln CDD_{t-i} + \delta u_{t-1} + \varepsilon_t \tag{5}$$

## 4. Data

Annual frequency data are collected from 1977 to 2016. Residential consumption in Las Cruces is measured in kilowatt-hours (KWH) using New Mexico billed sales data provided by EPEC. At least one recent study indicates that consumers respond to average prices (Ito, 2014). For this effort, average revenue per KWH is used as the own price variable. Revenue, KWH sales, and customer data are collected from EPEC archives and EPEC Form 1 filings with Federal Energy Regulatory Commission (FERC, 2017). All sample data employed are listed in Table 6 as an appendix to the study.

Real per capita income is used to account for income effects on residential electricity consumption. Real per capita income is calculated in constant 2009 dollars using the personal consumption expenditures (PCE) deflator (BEA, 2018b). The price variables are also deflated to constant 2009 dollars using the PCE deflator. Per capita income data for Las Cruces and the personal consumption expenditures deflator are collected from the Bureau of Economic Analysis (BEA, 2018a). Table 1 lists all of the data and units of measure.

**Table 1.** Variable Definitions and Sources

| Variable | Definition | Source |
|---|---|---|
| KWHC | Las Cruces electricity consumption per customer, measured in KWH sales per residential customer | El Paso Electric |
| KWH | Las Cruces electricity consumption, measured in KWH sales | El Paso Electric |
| PE | Real Electricity Price, measured in average $ revenue per KWH sold, base year 2009 | El Paso Electric FERC Form-1 Filings |
| LCPNG | Las Cruces Real Natural Gas Price, measured in average $ price per CCF, base year 2009 | Las Cruces Utilities, Energy Information Association |
| YCAP | Las Cruces Real Per Capita Income, measured in thousands of dollars, base year 2009 | U.S. Bureau of Economic Analysis |
| HDD | Heating Degree Days, Sum of Average Daily Temperatures under 65° Base | National Oceanic and Atmospheric Administration Northeast Regional Climate Center |
| CDD | Cooling Degree Days, Sum of Average Daily Temperatures over 65° Base | National Oceanic and Atmospheric Administration Northeast Regional Climate Center |
| CUST | Average Number of Residential Customers, thousands | El Paso Electric FERC Form-1 Filings |
| POP | Las Cruces Population, thousands | U.S. Bureau of Economic Analysis |

In Las Cruces, natural gas is a substitute for electricity. Accordingly, a natural gas price per 100 cubic feet (CCF) variable is also included in the sample. Historical data are collected from Las Cruces Utilities for 1996 through 2016 period. To approximate missing data, natural gas price data for New Mexico are collected from the Energy Information Administration (EIA, 2017). Equation 1 specifies the Las Cruces natural gas price as a function of the state gas price and is used to provide estimates for the missing values between 1977 and 1995 (Friedman, 1962). Table 2 displays the estimated regression results. The natural gas price for New Mexico coefficient is statistically significant at the 5-percent level. A chi-squared autocorrelation test confirms that the residuals for Equation (6) are not serially correlated.

$$LCPNG_t = b_0 + b_1 NMPNG_t + u_t \tag{6}$$

**Table 2.** Las Cruces Natural Gas Price Regression Output

| | | | | |
|---|---|---|---|---|
| Dependent Variable: LCNGP | | | | |
| Method: Least Squares | | | | |
| Sample (adjusted): 1996 2016 | | | | |
| Included observations: 21 after adjustments | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| C | -0.316 | 0.071 | -4.463 | 0.0003 |
| NMNGP | 0.857 | 0.077 | 11.169 | 0.000 |
| R-squared | 0.8678 | Mean dependent var | | 0.4535 |
| Adjusted R-squared | 0.8609 | S.D. dependent var | | 0.1979 |
| S.E. of regression | 0.0738 | Akaike info criterion | | -2.284 |
| Sum squared resid | 0.1035 | Schwarz criterion | | -2.185 |
| Log likelihood | 25.982 | Hannan-Quinn criter. | | -2.262 |
| F-statistic | 124.744 | Durbin-Watson stat | | 1.500 |
| Prob(F-statistic) | 0.000 | | | |

Note: These results are used to simulate Las Cruces natural gas prices for 1977-1995.

Prior studies indicate that weather influences residential electricity consumption in statistically significant manners (Contreras et al, 2009; Pourazarm and Cooray, 2013). To account for weather in the demand equation for electricity demand, data for heating degree days (HDD) and cooling degree days (CDD) are collected by the New Mexico State University (NMSU) weather station and downloaded from the National Oceanic and Atmospheric Administration Northeast Regional Climate Center (NOAA, 2018). HDD measures the number of degrees that each daily average temperature is below 65 degrees Fahrenheit. CDD measures the number of degrees that each daily average temperature is above 65 degrees Fahrenheit.

The summary statistics presented in Table 3 show that the average electricity consumption per customer in Las Cruces is 7,189 KWH per year, the standard deviation is 664 KWH per customer, with a median of 7,113 KWH. The minimum electricity consumption per customer for this sample period is 5,879 KWH and the maximum is 8,430 KWH, a range of 2,551 KWH. The skewness coefficient is 0.26, indicating a slightly right skewed distribution that is roughly symmetric. The kurtosis is 2.08, indicating the data are fairly platykurtic relative to a Gaussian distribution, but the coefficient of variation is still only 0.09.

**Table 3.** Data Summary Statistics

| | KWHC | PE | PNG | YCAP |
|---|---|---|---|---|
| Mean | 7,189 | 0.142 | 0.425 | 22,377 |
| Standard Deviation | 664.3 | 0.026 | 0.168 | 4,595 |
| Coef. of Variation | 0.092 | 0.186 | 0.395 | 0.205 |
| Median | 7,113 | 0.131 | 0.380 | 20,568 |
| Maximum | 8,430 | 0.193 | 0.824 | 29,654 |
| Minimum | 5,879 | 0.107 | 0.215 | 16,246 |
| Range | 2,551 | 0.087 | 0.609 | 13,408 |
| Skewness | 0.265 | 0.677 | 1.078 | 0.287 |
| Kurtosis | 2.083 | 2.055 | 3.179 | 1.513 |

| | HDD | CDD | CUST |
|---|---|---|---|
| Mean | 2,699 | 1,929 | 56,538 |
| Standard Deviation | 275.5 | 220.5 | 18,522 |
| Coef. of Variation | 0.102 | 0.114 | 0.328 |
| Median | 2,683 | 1,859 | 56,485 |
| Maximum | 3,346 | 2,362 | 84,673 |
| Minimum | 2,196 | 1,502 | 25,152 |
| Range | 1,150 | 860 | 59,521 |
| Skewness | 0.110 | 0.188 | -0.026 |
| Kurtosis | 2.300 | 1.870 | 1.749 |

Notes:

The sample period is 1977 – 2016.

All income and price data are measured in 2009 constant dollars.

The average real price of electricity in 2009 constant dollars is estimated to be $0.14 per KWH, the standard deviation is $0.03 per KWH, with a median of $0.13. The minimum average real price of electricity is $0.11 per KWH and the maximum is $0.19 per KWH, a range of $0.09 per KWH. The skewness is 0.68, indicating that the real price of electricity is slightly right skewed. The kurtosis is 2.06 indicating the data are platykurtic and the coefficient of variation is 0.18.

The real average price of natural gas in Las Cruces is $0.43 per CCF, the standard deviation is 0.17, with a median of $0.38 per CCF. The minimum price of natural gas in Las Cruces during the sample period is $0.22 per CCF and the maximum is $0.82 per CCF, giving a range of $0.60 per CCF. The skewness of the price of natural gas in Las Cruces is 1.08, indicating that the distribution is right skewed. The kurtosis is 3.18 and the coefficient of variation is 0.40.

The average Las Cruces real income per capita is $22,377. The standard deviation is $4,595 and the median is $20,568. The minimum per capita income is $16,246 and the maximum is $29,654, implying a range of $13,408. The skewness of Las Cruces income per capita is 0.29, reflecting overall symmetry. The kurtosis is found to be 1.51 indicating the data are fairly platykurtic, but the coefficient of variation is still only 0.21.

The average number of heating degree days in Las Cruces is 2,699 per year. The standard deviation is 275 days with a median of 2,683 days. The minimum number of heating degree days is 2,196 days with a maximum of 3,346 days, and the range is 1,150 days. With a skewness statistic of 0.11, HDD is largely symmetric. The fourth moment of 2.30 indicates that the distribution of HDD is platykurtic, but the coefficient of variation is only 0.10.

The average number of cooling degree days in Las Cruces is 1,929 per year. The standard deviation is 221 days with a median of 1,859. The minimum number of cooling degree days is 1,502 with a maximum of 2,362, yielding a range of 860 days. The CDD skewness is 0.19, substantially symmetric. The kurtosis is 1.87, indicating relatively thick distribution tails, but the coefficient of variation is a fairly small 0.11.

The average number of residential customers in Las Cruces during the 1977-2016 sample period is 56,538. The standard deviation is 18,522 with a median of 56,485 customers. The minimum number of customers is 25,152, the maximum number is 84,673, and the range is 59,521. The skewness statistic of -0.03, indicates near perfect symmetry. The customer data are platykurtic and the coefficient of variation is 0.33.

## 5. Empirical Results

Initial testing with CDD and HDD employed as separate independent variables, as shown in Equations 3, was not successful due to multicollinearity. To reduce this problem, the weather variables are combined into one degree days variable, DD = CDD + HDD. This procedure has been employed previously for residential electricity usage analysis (Fullerton et al, 2016). Although this step imposes parameter homogeneity with respect to hot and cold weather effects on household electricity consumption, the coefficient estimates are more plausible, estimation diagnostics improve, and this convention is employed for the remainder of the study. Imposing weather impact symmetry in this manner may not, however, always be advisable (Chang et al, 2016).

Phillips-Perron unit root tests indicate that the variables are integrated of an order of I(0) or I(1), allowing empirical analysis to be conducted using an ARDL modeling approach. The maximum lag length selected, using an Akaike information criterion, for any of the explanatory variables is three years. The resulting specification is an ARDL (3, 3, 3, 3, 2) model for residential electricity consumption in the Las Cruces service area.

A Breusch-Godfrey serial correlation LM test is conducted for a null hypothesis of no serial correlation. The computed Chi-squared statistic for up to five years indicates no serial correlation. The F-statistic for $H_0$: $b_5 = b_6 = b_7 = b_8 = b_9 = 0$ is 3.74. In the bounds test context, this value is higher than the 10-percent upper bound critical value, indicating cointegration.

Furthermore, the CUSUM and CUSUMSQ test results presented in Figure 1 and Figure 2 show stability with no computed statistics surpassing the 5-percent bounds.

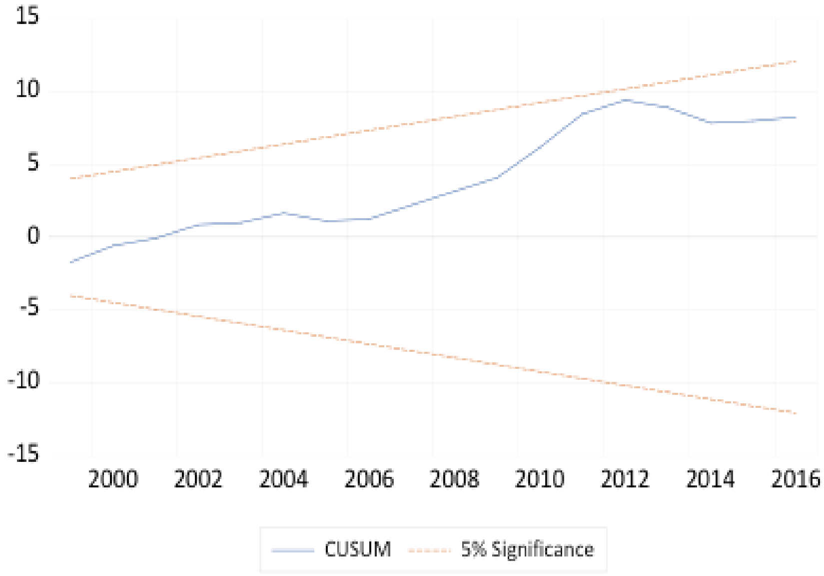


**Figure 1.** CUSUM Results for Resdential Electricity Consumption

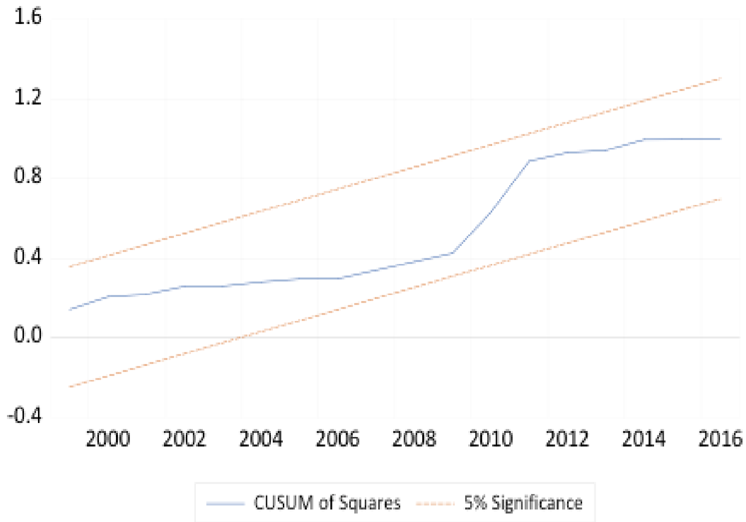


**Figure 2.** CUSUMSQ Results for Residential Electricity Consumption

The long-run coefficients for the estimated ARDL model are listed in Table 4. Although all of the long-run parameters exhibit the hypothesized signs discussed in the previous section, the links are not very reliable and do not satisfy the 5-percent significance criterion. The own-price elasticity coefficient is -0.08, indicating that a 10 percent increase in the price of electricity will be associated with less than a 1 percent reduction in residential electricity usage. That indicates that Las Cruces household electricity demand hardly responds to rate increases. A flat demand curve is not completely surprising for this region of the United States. Fullerton et al (2016) document an upward sloping demand function for nearby El Paso. Horizontal electricity demand curves for normal goods can occur when the income effect offsets the substitution effect (Vandermeulen, 1972). During the sample period, the real price of electricity did not keep pace with real per capita income and that may contribute to this outcome (Fullerton et al, 2015).

**Table 4.** ARDL Long-Run Coefficients for ARDL(3, 3, 3, 3, 2) Model

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LOG(PE) | -0.0843 | 0.3514 | -0.2400 | 0.8131 |
| LOG(PNG) | 0.0280 | 0.1021 | 0.2739 | 0.7873 |
| LOG(YCAP) | 0.3806 | 0.3438 | 1.1070 | 0.2829 |
| LOG(DD) | 0.4601 | 0.3361 | 1.3689 | 0.1879 |

The long-run parameter estimate for the price of natural gas in Table 4 is 0.028. That is highly inelastic and indicates that fluctuations in natural gas prices do not affect residential electricity usage very much in this EPEC service area. That cross-price coefficient indicates that a 1 percent increase in the price of natural gas will be accompanied by a 0.028 percent increase in residential electricity demand. While very small, the positive sign of the cross-price elasticity implies that, over the long-run, natural gas and electricity are treated as highly imperfect substitute goods by residences in Las Cruces. The magnitude of the cross-price elasticity is much smaller than what is reported for the geographically adjacent EPEC service area in El Paso (Fullerton et al., 2016).

The long-run slope coefficient estimate for real per capita income in Table 4 has a reasonable size (Espey and Espey, 2004). The income elasticity parameter is positive, suggesting that, over the long-run, electricity is treated as a normal good by Las Cruces households. That is opposite of what is reported for the nearby El Paso service area (Fullerton et al, 2016) and underscores the importance of conducting independent research for individual metropolitan economies, at least within the realm of energy economics. The income coefficient in Table 4 is 0.38, indicating that electricity is a necessity for las Cruces households (Phu, 2020). It further indicates that a 10-percent increase in real per capita income will lead to a 3.8 percent increment in residential electricity demand in the long-run. Because Las Cruces is a growing urban economy, that implies that EPEC will face more generating capacity pressures from this service area than the neighboring one to the south.

The composite explanatory variable for the weather, cooling degree days plus heating degree days, exhibits the hypothesized parameter sign with a coefficient of 0.46. The DD parameter indicates an inelastic response as a 10 percent increase in annual degree days will increase residential electricity demand by 4.6 percent. The coefficient magnitude indicates that there inclement weather leads to fairly substantial impacts on long-run residential electricity consumption in the Las Cruces service area.

Estimation results for the short-run error correction model are listed in Table 5. The own-price coefficients sum to -0.45 and satisfy the 5-percent criterion. That is relatively close to the short-run elasticities reported for multiple regions across the United States (Espey and Espey, 2004).

**Table 5.** ARDL Error Correction Model Coefficients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.0371 | 0.7172 | 2.8402 | 0.0109 |
| DLOG(KWHC(-1)) | -0.6301 | 0.1294 | -4.8707 | 0.0001 |
| DLOG(KWHC(-2)) | -0.1873 | 0.1035 | -1.8093 | 0.0871 |
| DLOG(PE) | -0.4947 | 0.1372 | -3.6060 | 0.0020 |
| DLOG(PE(-1)) | 0.2763 | 0.0929 | 2.9741 | 0.0081 |
| DLOG(PE(-2)) | -0.2334 | 0.0909 | -2.5674 | 0.0194 |
| DLOG(PNG) | 0.0498 | 0.0232 | 2.1477 | 0.0456 |
| DLOG(PNG(-1)) | -0.0498 | 0.0232 | -2.1511 | 0.0453 |
| DLOG(PNG(-2)) | 0.0405 | 0.0317 | 1.2760 | 0.2182 |
| DLOG(YCAP) | 0.0882 | 0.2246 | 0.3926 | 0.6992 |
| DLOG(YCAP(-1)) | -0.3988 | 0.2100 | -1.8991 | 0.0737 |
| DLOG(YCAP(-2)) | 0.3216 | 0.2089 | 1.5395 | 0.1411 |
| DLOG(DD) | 0.3602 | 0.0879 | 4.0959 | 0.0007 |
| DLOG(DD(-1)) | 0.2736 | 0.1292 | 2.1168 | 0.0485 |
| u(-1) | -0.5543 | 0.1950 | -2.8422 | 0.0108 |
| Diagnostic statistics for the underlying ARDL model: | | | | |
| R-squared | 0.9208 | Mean dependent var | | 0.0035 |
| Adjusted R-squared | 0.8704 | S.D. dependent var | | 0.0615 |
| S.E. of regression | 0.0221 | Akaike info criterion | | -4.4936 |
| Sum squared resid | 0.0108 | Schwarz criterion | | -3.8406 |
| Log likelihood | 98.1324 | Hannan-Quinn criter. | | -4.2634 |
| F-statistic | 18.2729 | Durbin-Watson stat | | 1.6879 |
| Prob(F-statistic) | 0.0000 | | | |

The natural gas price coefficients sum to 0.04 and exhibit the hypothesized positive sign. The highly inelastic value indicates that natural gas price fluctuations do not affect residential electricity usage very noticeably in Las Cruces. Collectively, the results indicate that, in the short-run, natural gas is treated as a weak substitute for electricity by households in the Mesilla Valley. That result is similar to what has been reported for other regions (Phu, 2020).

The real per capita income coefficients sum to 0.01 and exhibit the hypothesized positive sign, albeit with computed t-statistics that fail to surpass the 5-percent significance threshold. The highly inelastic estimate indicates that income fluctuations do not affect residential electricity demand in the short-run in Las Cruces. Although the estimate indicates that the relationship is not overly strong, electricity is found to be treated as both a normal good and a necessity in the short-run by Las Cruces households.

The composite explanatory variable used to account for weather effects on residential electricity demand is DD, the sum of annual cooling degree days and heating degree days. Fluctuations in DD are found to reliably impact residential electricity consumption in the short-run. The coefficients that sum to 0.63 and are positive as hypothesized. Both hot and cold weather lead residential customers to increase the use of electricity in this desert economy. The sensitivity of households to extreme weather is more pronounced, and statistically reliable, in Las Cruces than what has been reported for more temperate regions of the global economy (Csereklyei, 2020).

The error correction parameter is negative as hypothesized. The magnitude of the error correction coefficient indicates that 55 percent of any deviation from the long-run equilibrium will dissipate within a year. As a result, approximately 1.8 years are necessary for any departures from equilibrium to fully dissipate. That is a shorter amount of time than what has been documented for residential electricity consumption the nearby metropolitan economy of El Paso (Fullerton et al, 2016).

## 6. Conclusion

Residential electricity usage continues to be the focus of substantial research effort. Given the importance of electric energy in modern economies, that is to be expected. Advances in econometric methods and data availability also encourage more effort in this branch of the discipline.

Historically, one of the gaps in this literature has been empirical analysis of residential electricity demand in small and medium sized metropolitan economies. That has probably resulted from limited data coverage in these areas. In spite of being the second largest economy in the state, Las Cruces, New Mexico is one of those urban areas for which comparatively little energy consumption research has been conducted.

The results obtained vary in several notable ways from what has been documented for El Paso, Texas, a larger metropolitan economy which is located a mere 40 miles away from the Mesilla Valley. Those outcomes highlight the importance of examining more smaller urban economies individually rather than assuming that regional energy demand always follows the same usage patterns. Additional studies of electricity consumption in Las Cruces region are warranted. An obvious candidate is small commercial and industrial usage, as well as public and non-profit consumption. Important demand differences for those customer categories cannot be ruled out at this juncture.

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## Appendix

**Table 6.** Historical Data Appendix

| Year | KWHC | PE | PNG | YCAP | HDD | CDD |
|---|---|---|---|---|---|---|
| 1977 | 7,537.50 | 0.123 | 0.215 | 16.246 | 2987 | 1755 |
| 1978 | 7,887.04 | 0.141 | 0.272 | 16.714 | 3029 | 1795 |
| 1979 | 7,139.32 | 0.124 | 0.274 | 16.530 | 3346 | 1502 |
| 1980 | 6,085.53 | 0.158 | 0.332 | 16.307 | 3100 | 1762 |
| 1981 | 7,214.34 | 0.181 | 0.376 | 16.901 | 2717 | 1742 |
| 1982 | 5,879.24 | 0.183 | 0.523 | 17.126 | 3024 | 1685 |
| 1983 | 6,739.17 | 0.193 | 0.580 | 17.847 | 3069 | 1723 |
| 1984 | 6,619.95 | 0.193 | 0.610 | 18.082 | 3029 | 1806 |
| 1985 | 6,782.23 | 0.187 | 0.606 | 18.478 | 3008 | 1649 |
| 1986 | 6,450.10 | 0.184 | 0.533 | 18.888 | 2683 | 1765 |
| 1987 | 6,555.52 | 0.178 | 0.400 | 18.874 | 3046 | 1662 |
| 1988 | 6,652.86 | 0.177 | 0.408 | 18.387 | 2825 | 1715 |
| 1989 | 6,627.82 | 0.170 | 0.444 | 19.119 | 2606 | 2072 |
| 1990 | 6,531.52 | 0.166 | 0.405 | 19.192 | 2788 | 1943 |
| 1991 | 6,572.14 | 0.163 | 0.349 | 19.263 | 2862 | 1616 |
| 1992 | 6,752.98 | 0.152 | 0.254 | 19.812 | 2952 | 1786 |
| 1993 | 6,655.92 | 0.149 | 0.323 | 19.796 | 2670 | 1876 |
| 1994 | 6,796.17 | 0.142 | 0.327 | 19.610 | 2513 | 2200 |
| 1995 | 6,594.22 | 0.141 | 0.250 | 20.491 | 2298 | 1839 |
| 1996 | 6,757.35 | 0.131 | 0.271 | 20.393 | 2254 | 1841 |
| 1997 | 6,810.04 | 0.132 | 0.324 | 20.646 | 2314 | 1979 |
| 1998 | 6,836.74 | 0.134 | 0.316 | 21.582 | 2464 | 1813 |
| 1999 | 6,743.44 | 0.124 | 0.313 | 21.632 | 2196 | 1727 |
| 2000 | 7,092.48 | 0.120 | 0.303 | 22.163 | 2444 | 2231 |
| 2001 | 7,133.73 | 0.126 | 0.297 | 24.256 | 2606 | 2181 |
| 2002 | 7,321.17 | 0.123 | 0.316 | 24.951 | 2683 | 2185 |
| 2003 | 7,477.78 | 0.125 | 0.574 | 25.596 | 2458 | 2275 |
| 2004 | 7,393.69 | 0.122 | 0.652 | 26.379 | 2755 | 1826 |
| 2005 | 7,587.76 | 0.127 | 0.818 | 27.393 | 2634 | 2068 |
| 2006 | 7,548.59 | 0.129 | 0.824 | 27.344 | 2479 | 1954 |
| 2007 | 7,847.10 | 0.126 | 0.733 | 27.840 | 2629 | 2021 |
| 2008 | 7,609.74 | 0.130 | 0.819 | 27.855 | 2683 | 1737 |
| 2009 | 7,904.30 | 0.121 | 0.421 | 28.575 | 2622 | 2090 |
| 2010 | 8,293.19 | 0.119 | 0.452 | 28.845 | 2834 | 2081 |
| 2011 | 8,430.32 | 0.116 | 0.406 | 28.694 | 2854 | 2362 |
| 2012 | 8,390.02 | 0.111 | 0.283 | 28.690 | 2420 | 2209 |
| 2013 | 8,200.32 | 0.114 | 0.384 | 27.304 | 2876 | 2134 |
| 2014 | 7,866.91 | 0.118 | 0.441 | 28.052 | 2350 | 2075 |
| 2015 | 8,096.35 | 0.110 | 0.298 | 29.586 | 2571 | 2227 |
| 2016 | 8,139.24 | 0.107 | 0.277 | 29.654 | 2301 | 2234 |

| Year | CUST | POP | KWH | PCE |
|---|---|---|---|---|
| 1977 | 25,333 | 88.30 | 190,947,495 | 0.341 |
| 1978 | 25,152 | 92.19 | 198,374,947 | 0.365 |
| 1979 | 29,069 | 93.74 | 207,532,884 | 0.397 |
| 1980 | 35,358 | 97.01 | 215,172,027 | 0.440 |
| 1981 | 29,730 | 99.62 | 214,482,216 | 0.478 |
| 1982 | 37,478 | 103.45 | 220,342,299 | 0.505 |
| 1983 | 33,951 | 107.63 | 228,801,449 | 0.526 |
| 1984 | 35,949 | 112.47 | 237,980,754 | 0.546 |
| 1985 | 37,714 | 116.32 | 255,784,886 | 0.566 |
| 1986 | 39,472 | 120.47 | 254,598,483 | 0.578 |
| 1987 | 41,221 | 125.03 | 270,224,895 | 0.596 |
| 1988 | 42,985 | 130.02 | 285,973,059 | 0.620 |
| 1989 | 44,515 | 132.96 | 295,037,547 | 0.646 |
| 1990 | 45,837 | 136.59 | 299,385,489 | 0.674 |
| 1991 | 47,270 | 141.23 | 310,665,224 | 0.697 |
| 1992 | 48,912 | 147.00 | 330,301,610 | 0.715 |
| 1993 | 50,616 | 153.05 | 336,895,928 | 0.733 |
| 1994 | 52,431 | 157.53 | 356,329,852 | 0.748 |
| 1995 | 54,150 | 161.01 | 357,076,759 | 0.764 |
| 1996 | 55,769 | 165.62 | 376,850,884 | 0.780 |
| 1997 | 57,201 | 169.08 | 389,541,224 | 0.793 |
| 1998 | 58,588 | 172.06 | 400,551,097 | 0.799 |
| 1999 | 60,409 | 173.89 | 407,364,168 | 0.811 |
| 2000 | 61,889 | 175.10 | 438,946,495 | 0.831 |
| 2001 | 62,856 | 176.50 | 448,398,005 | 0.847 |
| 2002 | 64,294 | 178.46 | 470,707,370 | 0.859 |
| 2003 | 65,879 | 182.05 | 492,628,734 | 0.876 |
| 2004 | 68,255 | 184.94 | 504,656,261 | 0.897 |
| 2005 | 71,120 | 189.20 | 539,641,286 | 0.923 |
| 2006 | 73,062 | 193.70 | 551,514,903 | 0.947 |
| 2007 | 75,664 | 197.85 | 593,743,154 | 0.971 |
| 2008 | 77,283 | 200.86 | 588,103,907 | 1.001 |
| 2009 | 78,529 | 205.40 | 620,716,793 | 1.000 |
| 2010 | 79,601 | 210.20 | 660,146,425 | 1.017 |
| 2011 | 80,169 | 212.98 | 675,850,676 | 1.041 |
| 2012 | 80,694 | 214.43 | 677,024,526 | 1.061 |
| 2013 | 81,992 | 214.05 | 672,360,615 | 1.075 |
| 2014 | 82,817 | 214.06 | 651,513,800 | 1.092 |
| 2015 | 83,632 | 214.30 | 677,113,937 | 1.095 |
| 2016 | 84,673 | 214.21 | 689,174,035 | 1.108 |