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Residential Electricity Consumption In Las Cruces

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by

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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 responds in a statistically reliable manner only to real per capita income. In the short-run, residential consumption responds reliably to all of the variables except heating degree days. Somewhat surprisingly, the short-run results also include an own-price elasticity that is slightly positive, implying that residential electricity has an upward sloping demand curve in Las Cruces.

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Chapter 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.

In this study, residential electricity sales are examined for the Las Cruces, New Mexico metropolitan economy. Las Cruces is part of Dona Ana County and has an approximate population of 216,804 with an estimated nominal per capita income of $34,016 (Fullerton and Walke, 2015). Las Cruces is close in distance to another metropolitan economy El Paso, Texas where residential electricity consumption has previously been analyzed (Fullerton et al., 2016).

El Paso Electric (EPE) services Las Cruces, New Mexico. EPE is a regional electric utility that provides electricity to 400,000 retail and wholesale customers within a 10,000 square mile area. EPE provides services to territories ranging from Hatch, New Mexico to Van Horn, Texas and has a peak generating capacity of 2,010 MW (EPEC, 2016).

To examine Las Cruces residential electricity consumption, an autoregressive distributed lag (ARDL) bounds testing approach is used. The ARDL approach allows analyzing long-run and short-run consumption relationships. Annual data from 1977-2016 from EPE are collected for the Las Cruces service area. In depth analysis of Las Cruces kilowatt hour (KWH) consumption has not previously been undertaken.

Subsequent sections of the study are as follows. A partial review 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. A summary of principal outcomes comprises the final section.

Chapter 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. Shin (1985) examines the information problem by focusing on consumer's perception of prices and multi-step block rate schedules. Results, in this and other studies, indicate that consumers respond to the average prices of their electricity bills (Ito, 2014).

Research also examines the effects of income and other variables on household electricity usage (Hultman and Ramsey, 1977). Results find 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), the results imply that a decrease in real income would increase electricity demand suggesting that electricity is an “inferior good”. A separate study using national data also presents 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 and determine 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).

A recent effort on U.S. residential electricity demand focuses 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 suggests that households will tend to invest in less energy-intensive appliances.

Recent regional studies also employ out-of-sample model simulation as additional tool 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 model developed. A similar study for residential electricity demand in Iran reports temperature as the biggest determinant of electricity demand (Cooray and Pourazarm, 2013). It includes a seven-year dynamic forecast. Recent research on residential electricity demand in El Paso uses an ARDL procedure (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 Walke, 2015). 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.

Chapter 3: 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 El Paso Electric (EPE). 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 EPE and EPE Form 1 filings with Federal Energy Regulatory Commission (FERC, 2017).

Real per capita income variable 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
PNG	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. The existing historical data are collected from Las Cruces Utilities and cover 1996-2016. 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 1 are not serially correlated.

$$LCNGP_t = b_0 + b_1 NMNGP_t + u_t \tag{1}$$

Table 2: Natural Gas Price Regression

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: Sample period is 1996-2016

Prior studies indicate that weather influences residential electricity consumption in statistically significant manners (Contreras et al., 2009; Cooray and Pourazarm, 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.

Table 3: Data Summary Statistics

	KWHC	PE	PNG	YCAP
Mean	7188.9	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	7113.1	0.131	0.380	20.568
Maximum	8430.3	0.193	0.824	29.654
Minimum	5879.2	0.107	0.215	16.246
Range	2551.1	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	POP	KWH
Mean	2699.5	1928.6	56538.0	159.364	414,811,402
Standard Deviation	275.5	220.53	18522.0	41.431	167,491,391
Coef. of Variation	0.102	0.114	0.328	0.260	0.404
Median	2683	1858.5	56485	167.350	383,196,054
Maximum	3346	2362	84673	214.428	689,174,035
Minimum	2196	1502	25152	88.302	190,947,495
Range	1150	860	59521	126.126	498,226,540
Skewness	0.110	0.188	-0.026	-0.221	0.334
Kurtosis	2.300	1.870	1.749	1.748	1.716

Note: Sample Period is 1977-2016

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.

The average real price of electricity 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 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 of the data 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 found to be close to $22,377. The standard deviation is $4,595 with a median of $20,568. The minimum per capita income is $16,246 and the maximum is $29,654 giving 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, a range of 1,150 days. The skewness of HDD is 0.11, largely symmetric. The kurtosis is 2.30 making the distribution 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, 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 amount of customers is 25,152 and the maximum number is 84,673, a range of 59,521. The skewness is found to be -0.03, indicating near perfect symmetry. The coefficient of variation is 0.33. The average population in Las Cruces in the sample period is 159,364 people. The standard deviation is 41,431 with a median of 167,350 people. The minimum population is 88,302 people and the maximum population is 214,428, a range of 126,126 people.

Average total residential electricity consumption in Las Cruces is 414,811,402 kilowatt hours (KWH). The standard deviation is 167,491,391 KWH with a median of 383,196,054 KWH. The sample minimum consumption is 190,947,495 KWH and the maximum is 689,174,035 KWH. At 0.404, the coefficient of variation for KWH is relatively larger than those of the other variables in the sample.

A demand function is specified using the variables listed in Table 1. As noted above, electricity consumption functions generally use economic and weather variables to analyze long-run and short-run electricity demand. Because non-zero amount data are utilized, the variables are transformed using natural logarithms prior to estimation (Tukey, 1977). In the following section, a theoretical model is developed using an ARDL specification that has been successfully applied to the southern portion of the EPE service area (Fullerton et al., 2016).

Chapter 4: Theoretical Framework

A demand function for Las Cruces residential electricity consumption is specified using economic and weather variables. Natural logarithms are used to transform the data prior to estimation. Expected coefficient signs are listed below Equation (2).

$$\ln KWHC_t = a_0 + a_1 \ln PE_t + a_2 \ln PNG_t + a_3 \ln YCAP_t + a_4 \ln HDD_t + a_5 \ln CDD_t + u_t \quad (2)$$

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An autoregressive distributed lag model (ARDL) estimation approach is employed similar to that utilized for the nearby El Paso region (Fullerton et. al, 2016). The ARDL model employs a bounds testing procedure is applied that allows for cointegration regardless of the variables being stationary with I(0) or I(1) orders of integration (Dergiades and Tsolfides, 2008). The null hypothesis for no cointegration, $H_0: b_1 = b_2 =,,, b_j = 0$, is examined using an F-test. That null is rejected because the computed F-statistic is larger than the upper bound (Pesaran et. al, 2001).

Equation (3) shows the general ARDL specification (Pesaran et. al, 2001). In Equation (3), q represents the optimal number of dependent variable lags and pδ_i is used for the optimal number of explanatory variable lags. The error term is represented by v with t as the time subscript.

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

Equation (4) 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.

$$a_j = \sum_{i=0}^{p_j} \alpha_{ji} / (1 - \sum_{i=1}^{q} \gamma_i) \quad (4)$$

The variables in Equation (2) are tested for cointegration by employing a bounds test (Pesaran et al., 2001). Equation (5) is computed with Δ representing the first-difference operator and w the 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.

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

If a cointegrating relationship exists, a short-run error correction model is estimated. The residuals from Equation (2) are lagged and included as the error correction term represented by u_{t-1}. The hypothesized coefficient sign for the error correction term is negative. When that condition is met, δ is the rate at which a short-run departure from the long-run equilibrium will dissipate. Equation (6) shows the specification for the short-run error correction model.

$$\Delta \ln KWHC_t = \beta_0 + \sum_{i=0}^{q-1} \partial_i \Delta \ln KWHC_{t-i} + \sum_{i=0}^{p_1-1} \beta_{1i} \Delta \ln PE_{t-i} + \sum_{i=0}^{p2-1} \beta_{2i} \Delta \ln PNG_{t-i} + \sum_{i=0}^{p3-1} \beta_{3i} \Delta \ln YCAP_{t-i} + \sum_{i=0}^{p_4-1} \beta_{4i} \Delta \ln HDD_{t-i} + \sum_{i=0}^{p_5-1} \beta_{5i} \Delta \ln CDD_{t-i} + \delta u_{t-1} + \varepsilon_t \tag{6}$$

Chapter 5: Empirical Results

Phillips-Perron unit root tests indicate the variables are integrated of an order of I(0) or I(1), allowing suitable analysis within the framework of an ARDL model. A maximum of 3 lags for each variable was selected using the Akaike Information Criterion. The result is an ARDL (2,3,3,3,0,2) model for residential electricity consumption in the Las Cruces region.

The Breusch-Godfrey serial correlation LM test is conducted with 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 $H_o = b_6 = b_7 = b_8 = b_9 = b_{10} = b_{11} = 0$, is 3.64. In the bounds test context, this value is higher than the 10-percent upper bound critical value indicating cointegration. Furthermore, the CUSUM and CUSUMSQ tests in Figure 1 and Figure 2 show stability with no statistics surpassing the 5-percent bounds.

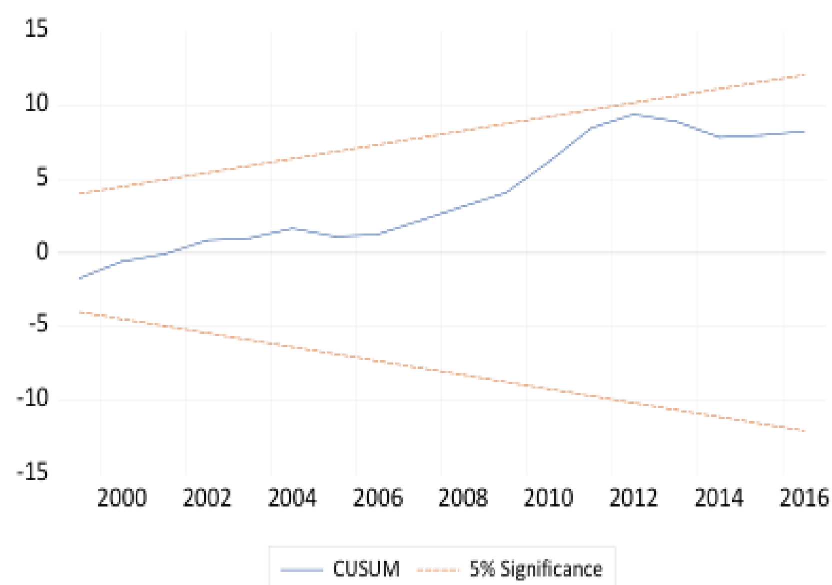

Figure 1: CUSUM Results for Resdential Electricity Consumption

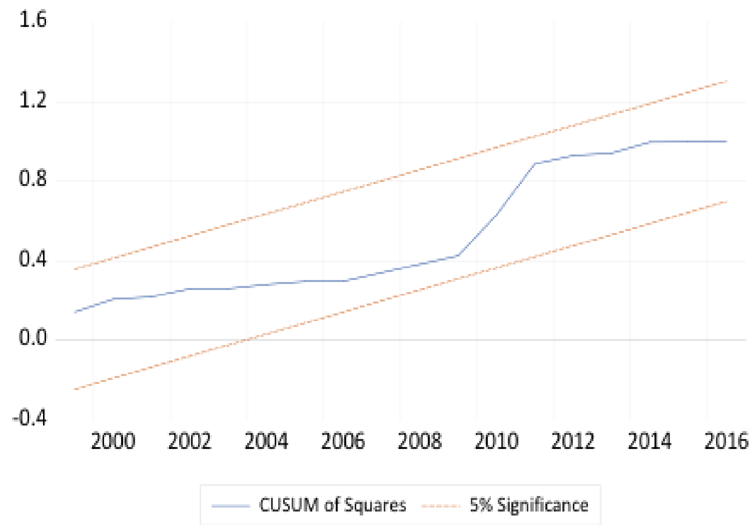

Figure 2: CUSUMSQ Results for Resdential Electricity Consumption

The long-run coefficients for the estimated ARDL model are listed in Table 4. Estimates indicate that only real per capita income is statistically significant at a 5-percent level with the hypothesized positive sign. The income elasticity parameter indicates an inelastic response as a 1-percent increase in real per capita income for the Las Cruces region would increase residential electricity demand by 0.69 percent in the long-run. This would suggest that electricity is treated as a normal good in Las Cruces in the long-run.

Table 4: ARDL Analysis of Residential Electricity Consumption

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

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(PE)	0.1953	0.1732	1.1279	0.2742
LOG(PNG)	-0.0669	0.0575	-1.1638	0.2597
LOG(YCAP)	0.6879	0.2125	3.2363	0.0046
LOG(HDD)	0.1394	0.0942	1.4803	0.1561
LOG(CDD)	0.0013	0.1866	0.0068	0.9946

Diagnostic statistics for the underlying ARDL model:

R-squared	0.9671	Mean dependent var	8.8722
Adjusted R-squared	0.9341	S.D. dependent var	0.0938
S.E. of regression	0.0241	Akaike info criterion	-4.3086
Sum squared resid	0.0104	Schwarz criterion	-3.4813
Log likelihood	98.7083	Hannan-Quinn criter.	-4.0169
F-statistic	29.3692	Durbin-Watson stat	1.5529
Prob(F-statistic)	0.0000		

Bounds test results:

F-statistic	3.635551	Lower Bound (0)	2.26
Significance	10%	Upper Bound (1)	3.35

The long-run parameters for other variables are not statistically significant but do exhibit some hypothesized signs. The own-price elasticity coefficient is 0.20 indicating a 1 percent increase in the price of electricity will increase residential electricity demand by 0.20 percent. This would suggest an upward electricity demand curve slope in the long-run for the Las Cruces region. Similar results are reported in other residential electricity studies (Fullerton et. al, 2015). Among other things, upward sloping electricity demand curves for normal goods can occur when the income effect exceeds the substitution effect.

The long-run parameter for the price of natural gas is -0.07 indicating an inelastic response. The parameter signifies that a 1 percent increase in the price of natural gas will decrease residential electricity demand by 0.07 percent. The results indicate that natural gas and electricity are treated as complement goods in the long-run in the Las Cruces region.

Both explanatory variables for the weather, heating degree days and cooling degree days, exhibit the hypothesized parameter signs with coefficients of 0.14 and 0.0001 respectively. The heating degree days parameter indicates an inelastic response as a 1 percent increase in annual heating degree days will increase residential electricity demand by 0.14 percent. The cooling degree days parameter indicates an inelastic response as a 1 percent increase in annual cooling degree days will increase residential electricity demand by 0.001 percent in the long-run. The small magnitude effect of cooling degree days on electricity consumption suggest that cooling appliances are not important for long-run electricity use in the Las Cruces region. The results indicate that while consumers will adjust home heating and cooling appliances during inclement weather there will be a small positively correlated impact on long-run residential electricity consumption in the Las Cruces region.

Table 5: ARDL Analysis of Error Correction Model Results

Error Correction Model:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.8472	0.9214	5.2609	0.0001
DLOG(KWHC(-1))	-0.3394	0.0915	-3.7069	0.0016
DLOG(PE)	0.0071	0.1209	0.0583	0.9541
DLOG(PE(-1))	0.2748	0.0696	3.9491	0.0009
DLOG(PE(-2))	-0.1902	0.0736	-2.5833	0.0187
DLOG(PNG)	-0.0019	0.0219	-0.0861	0.9324
DLOG(PNG(-1))	-0.0230	0.0222	-1.0381	0.3130
DLOG(PNG(-2))	0.0468	0.0232	2.0146	0.0591
DLOG(YCAP)	0.1350	0.1907	0.7077	0.4882
DLOG(YCAP(-1))	-0.4122	0.1968	-2.0944	0.0506
DLOG(YCAP(-2))	0.4022	0.1865	2.1572	0.0448
DLOG(CDD)	0.1235	0.0410	3.0133	0.0075
DLOG(CDD(-1))	0.1259	0.0409	3.0826	0.0064
u_{t-1}	-0.8139	0.1542	-5.2794	0.0001

Diagnostic statistics for the underlying ARDL model:

R-squared	0.9232	Mean dependent var	0.0035
Adjusted R-squared	0.8799	S.D. dependent var	0.0615
S.E. of regression	0.0213	Akaike info criterion	-4.5788
Sum squared resid	0.0104	Schwarz criterion	-3.9693
Log likelihood	98.7083	Hannan-Quinn criter.	-4.3639
F-statistic	21.2795	Durbin-Watson stat	1.5529
Prob(F-statistic)	0.0000		

Estimated results for the short-run error correction model are listed in Table 5. The own-price coefficients sum to 0.09 and do not exhibit the hypothesized negative sign. While greater than zero, the own-price parameter indicates that the relation is highly inelastic. Similar to what is reported for the long-run results in Table 4, the own-price elasticity coefficients collectively imply that residential electricity has an upward sloping curve in Las Cruces. Similar results have been reported in other residential electricity studies (Fullerton et. al, 2015). Although this may reflect the impact of greater energy efficiency in home appliances, more testing is warranted before reaching any firm conclusions.

The natural gas price coefficients sum to 0.02 and exhibit the hypothesized positive sign. The highly inelastic parameter estimate indicates that natural gas price fluctuations do not affect electricity usage very noticeably. Collectively, the results indicate that electricity and natural gas are treated as weak substitutes in the short-run in the Mesilla Valley.

The real per capita income coefficients sum to 0.13 and exhibit the hypothesized positive sign. The inelastic parameter estimate indicates that a 1 percent increase in real per capita income will increase residential electricity demand by 0.13 percent. Although the estimate indicates that the relationship is not overly strong, electricity is found to be treated as a normal good in the short-run by Las Cruces households.

The explanatory variables used to account for weather effects on residential electricity demand are heating degree days and cooling degree days. In the short-run, only cooling degree days are found to reliably impact residential electricity consumption with coefficients that sum to 0.25 and positive as hypothesized. Not surprisingly, that indicates that residential consumers will increase the use of cooling appliances during hot weather spells in this desert economy.

The error correction parameter is negative as hypothesized. The magnitude of the error correction coefficient indicates that 81 percent of any deviation from the long-run equilibrium will dissipate within a year. As a result, approximately 1.2 years are necessary for any departures from equilibrium to fully dissipate. That is a much shorter amount of time than what has been documented for the nearby metropolitan economy of El Paso (Fullerton et al., 2016).

Chapter 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 metropolitan economies. That has probably occurred due to data coverage in these areas. Las Cruces, New Mexico is one of those urban economies about which comparatively little energy consumption research has been conducted.

The results obtained vary in several notable ways from what has been documented for much larger El Paso, Texas 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 usage. Important demand differences for those customer categories cannot be ruled out at this juncture.

Bibliography

Alberini, A., Gans, W., & Velez-Lopez, D. 2011. Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics*, 33 (5), 870-881.

BEA. 2018a. *CA1 Personal Income Summary: Personal Income, Population, Per Capita Personal Income.* Washington, DC: United States Department of Commerce.

BEA. 2018b. *Personal Consumption Expenditures Implicit Price Deflator*. Washington, DC: United States Department of Commerce.

Borenstein, S. 2009. *To What Electricity Price Do Consumers Respond? Residential Demand Elasticity Under Increasing-Block Pricing*. Berkeley, CA: University of California Energy Institute.

Branch, E. R. 1993. Short run income elasticity of demand for residential electricity using consumer expenditure survey data. *Energy Journal,* 14 (4), 111-121.

Chang, H. S., & Hsing, Y. 1991. The demand for residential electricity: New evidence on time-varying elasticities. *Applied Economics,* 23 (7), 1251-1256.

Cicchetti, C.J., & Smith, V.K. 1975. Alternative price measures and the residential demand for electricity. *Regional Science and Urban Economics,* 5 (4), 503-516.

Contreras, S., Smith, W.D., Roth, T.P., & Fullerton, T.M., Jr. 2009. Regional evidence regarding U.S. residential electricity consumption. *Empirical Economics Letters,* 8 (9), 827-832.

Cooray, A., & Pourazarm, E. 2013. Estimating and forecasting residential electricity demand in Iran. *Economic Modelling,* 35, 546-558

Dergiades, T., & Tsoulfidis, L. 2008. Estimating residential demand for electricity in the United States, 1965-2006. *Energy Economics,* 30 (5), 2722-2730.

EIA. 2017. *New Mexico Price of Natural Gas Delivered to Residential Consumers*. Washington, DC: United States Department of Energy.

EPEC. 2016. *Investor Relations Fact Sheet*. El Paso, TX: El Paso Electric Company.

Espey, J.A., & Espey, M. 2004. Turning on the lights: a meta-analysis of residential electricity demand elasticities. *Journal of Agricultural and Applied Economics,* 36 (1), 65–81.

FERC. 2017. *Form 1 – Electric Utility Annual Report*. Washington, DC: Federal Energy Regulatory Commission.

Filippini, M. 1995. Swiss residential demand for electricity by time-of-use. *Resource and Energy Economics,* 17 (3), 281-290.

Friedman, M. 1962. The interpolation of time series by related series. *Journal of the American Statisical Association,* 57 (300), 729-757.

Fullerton, T.M. Jr., Juarez, D.A., & Walke, A.G. 2012. Residential electricity consumption in Seattle. *Energy Economics,* 34 (5), 1693-1699.

Fullerton, T.M., Jr., & Walke, A.G. 2015. *Borderplex Economic Outlook to 2016*. El Paso, TX: UTEP Border Region Econometric Modeling Project.

Fullerton, T.M., Jr., Resendez, I.M., & Walke, A.G. 2015. Upward sloping demand for a normal? Residential electricity in Arkansas. *International Journal of Energy Economics and Policy,* 5 (4), 1065-1072.

Fullerton, T.M., Jr., Macias, D.R., and Walke, A.G. 2016. Residential electricity demand in El Paso. *Journal of Regional Analysis & Policy,* 46 (2), 154-167.

Halicioglu, F. 2007. Residential electricity demand dynamics in Turkey. *Energy Economics,* 29 (2), 199-210.

Halvorsen, B. 1975. Residential demand for electric energy. *Review of Economics and Statistics,* 57 (1), 12-18.

Herriges, J., & King, K. 1994. Residential demand for electricity under inverted block rates: Evidence from a controlled experiment. *Journal of Business & Economic Statistics,* 12 (4), 419-430.

Hondroyiannis, G. 2004. Estimating residential demand for electricity in Greece. *Energy Economics,* 26 (3), 319-334.

Hultman, C.W. & Ramsey, J.R. 1977. An econometric analysis of the residential demand for electricity: A tutorial. *Public Data Use,* 5 (6), 32-40.

Ito, K. 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing, *American Economic Review*, 104 (2), 537-563.

Nayaran, P.K. 2005. The saving and investment nexus for China: Evidence from cointegration tests. *Applied Economics,* 37 (17), 1979-1990.

Narayan, P.K., & Smyth, R. 2005. The residential demand for electricity in Australia: An application of the bounds testing approach to cointegration. *Energy Policy,* 33 (4), 467-475.

NOAA. 2018. *NOAA Northeast Regional Climate Center*. Washington, DC: United States Department of Commerce

Pesaran, M.H., & Shin, Y. 1999. An autoregressive distributed lag modelling approach to cointegration analysis. *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium* (pp.371-413). Cambridge, UK: Cambridge University Press.

Pesaran, M.H., Shin, Y., & Smith, R.J. 2001. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16 (3), 289-326.

Roth, T.P. 1981. Average and marginal price changes and the demand for electricity: An econometric study. *Applied Economic,s* 13 (3), 377-388.

Shin, J.S. 1985. Perception of price when price information is costly: Evidence from residential electricity demand. *Review of Economics and Statistics*, 67 (4), 591-598.

Silk, J.I., & Joutz, F.L. 1997. Short and long-run elasticities in US residential electricity demand: A co-integration approach. *Energy Economics*, 19 (4), 493-513

Taylor, L.D. 1975. The demand for electricity: A survey. *Bell Journal of Economics*, 6 (1), 74-110.

Tukey, J.W. 1977. *Exploratory Data Analysis*. Reading, MA: Pearson.

Wilder, R.P. & Willenborg, J.F. 1975. Residential demand for electricity: A consumer panel approach. *Southern Economic Journal*, 42 (2), 212-217.

Appendix A: Data

Table 6: Annual Data

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

Appendix B: Alternative Specification and Estimation Results

Table 7: Alternative Long-Run ARDL Specification 1: ARDL(4,3,2,0,3,1) using AIC

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(PE)	-1.144731	1.019284	-1.123073	0.277
LOG(PNG)	0.375527	0.363636	1.032701	0.3162
LOG(YCAP)	-0.932161	1.273172	-0.732156	0.474
LOG(HDD)	0.492191	0.36551	1.346589	0.1958
LOG(CDD)	1.090716	1.010914	1.07894	0.2957

Diagnostic statistics for the underlying ARDL model:

R-squared	0.970834	Mean dependent var	8.876626
Adjusted R-squared	0.939952	S.D. dependent var	0.091195
S.E. of regression	0.022347	Akaike info criterion	-4.458982
Sum squared resid	0.00849	Schwarz criterion	-3.623236
Log likelihood	99.26167	Hannan-Quinn criter.	-4.167284
F-statistic	31.43683	Durbin-Watson stat	1.370076
Prob(F-statistic)	0		

Table 8: ARDL Bounds Test for ARDL(4,3,2,0,3,1)

Bounds test results:			I(0)	I(1)
F-statistic	3.317468	10%	2.26	3.35
k	5	5%	2.62	3.79
		2.50%	2.96	4.18
		1%	3.41	4.68

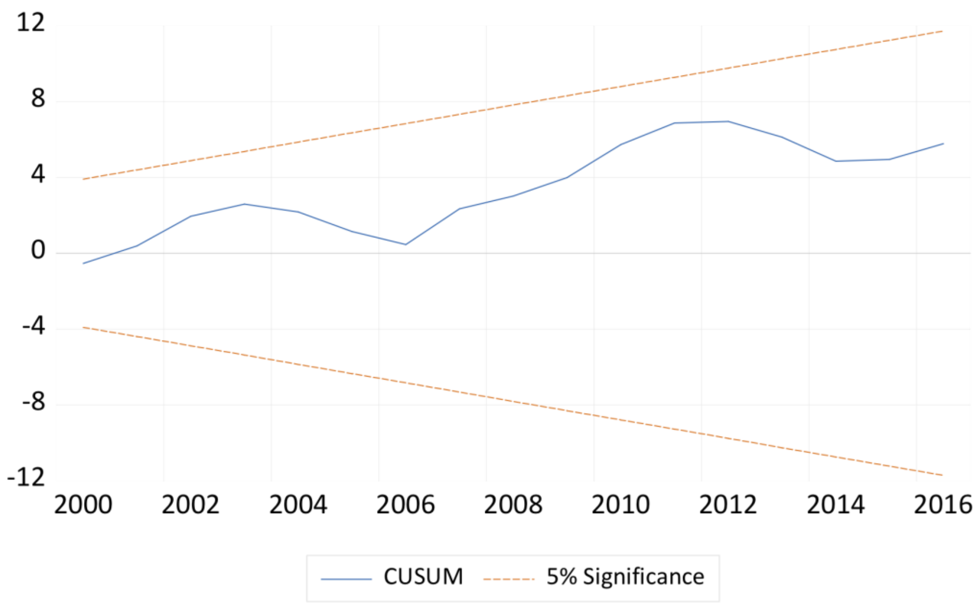

Figure 3: CUSUM for ARDL(4,3,2,0,3,1) (AIC)

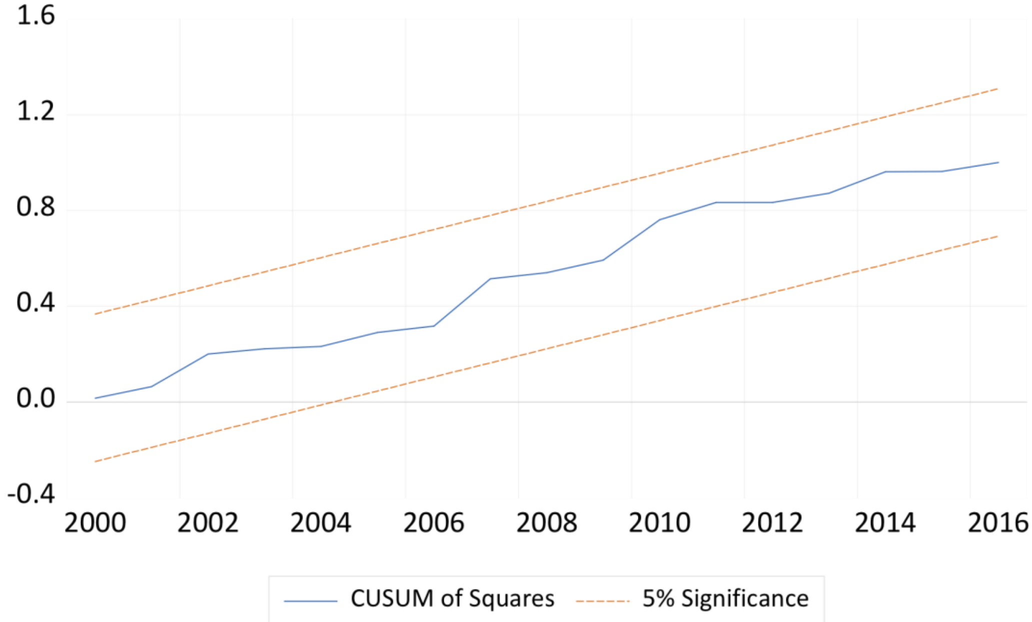

Figure 4: CUSUMSQ for ARDL(4,3,2,0,3,1) (AIC)

Table 9: Error Correction Model for ARDL(4,3,2,0,3,1) using AIC

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.735414	0.147921	-4.971683	0.0001
DLOG(KWHC(-1))	-0.890298	0.099179	-8.976676	0
DLOG(KWHC(-2))	-0.484465	0.137588	-3.521117	0.0026
DLOG(KWHC(-3))	-0.225691	0.095941	-2.3524	0.031
DLOG(PE)	-0.350332	0.164315	-2.132078	0.0479
DLOG(PE(-1))	-0.148728	0.111192	-1.337572	0.1987
DLOG(PE(-2))	-0.129384	0.066509	-1.945364	0.0685
DLOG(PNG)	0.035885	0.020631	1.739403	0.1
DLOG(PNG(-1))	-0.078802	0.021221	-3.713362	0.0017
DLOG(HDD)	0.140892	0.047757	2.950155	0.009
DLOG(HDD(-1))	0.215041	0.055419	3.880278	0.0012
DLOG(HDD(-2))	0.192454	0.058584	3.285092	0.0044
DLOG(CDD)	0.199927	0.046098	4.336976	0.0004
CointEq(-1)*	-0.328788	0.064781	-5.075348	0.0001

Diagnostic statistics for the underlying ARDL model:

R-squared	0.921796	Mean dependent var	0.008077
Adjusted R-squared	0.875585	S.D. dependent var	0.055693
S.E. of regression	0.019644	Akaike info criterion	-4.73676
Sum squared resid	0.00849	Schwarz criterion	-4.120947
Log likelihood	99.26167	Hannan-Quinn criter.	-4.521824
F-statistic	19.94736	Durbin-Watson stat	1.370076
Prob(F-statistic)	0		

Table 10: Alternative Long-Run ARDL Specification 2: ARDL(3,0,2,0,3,1) using HQ

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(PE)	0.119126	0.202033	0.589636	0.5614
LOG(PNG)	-0.01527	0.047889	-0.318868	0.7528
LOG(YCAP)	0.530896	0.190899	2.781025	0.0109
LOG(HDD)	0.136165	0.169072	0.805365	0.4292
LOG(CDD)	0.194344	0.159953	1.215002	0.2372

Diagnostic statistics for the underlying ARDL model:

R-squared	0.935845	Mean dependent var	8.872221
Adjusted R-squared	0.89502	S.D. dependent var	0.093826
S.E. of regression	0.0304	Akaike info criterion	-3.857804
Sum squared resid	0.020332	Schwarz criterion	-3.20473
Log likelihood	86.36938	Hannan-Quinn criter.	-3.627565
F-statistic	22.92299	Durbin-Watson stat	1.632327
Prob(F-statistic)	0		

Table 11: ARDL Bounds Test for ARDL(3,0,2,0,3,1)

Bounds test results:			I(0)	I(1)
F-statistic	11.34322	10%	2.26	3.35
k	5	5%	2.62	3.79
		2.50%	2.96	4.18
		1%	3.41	4.68

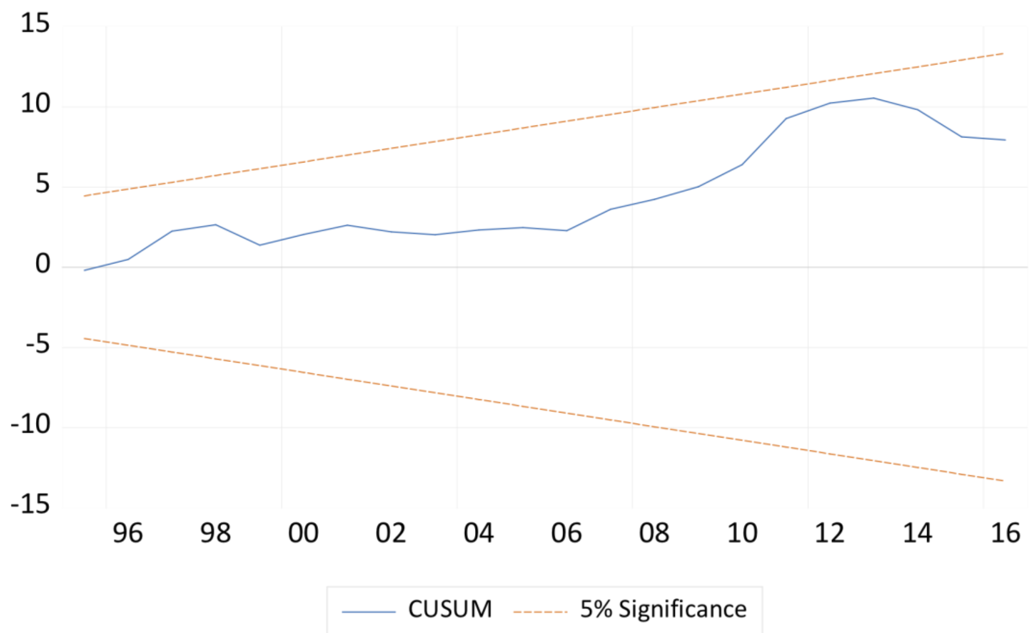

Figure 5: CUSUM for ARDL(3,0,2,0,3,1) (HQ)

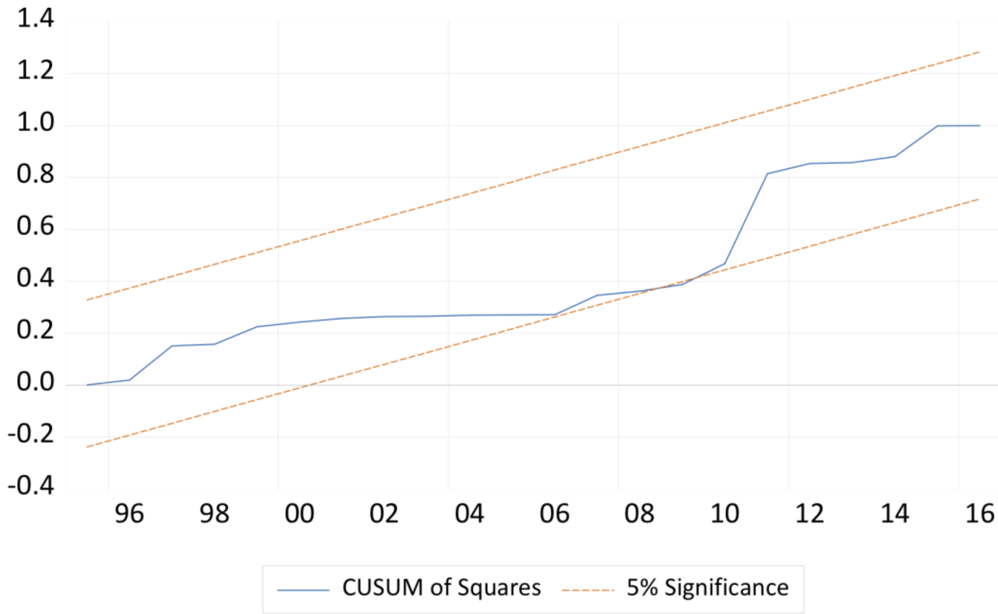

Figure 6: CUSUMSQ for ARDL(3,0,2,0,3,1) (HQ)

Table 12: Error Correction Model for ARDL(3,0,2,0,3,1) using HQ

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.80865	0.525464	9.151253	0
DLOG(KWHC(-1))	-0.438934	0.094571	-4.641337	0.0001
DLOG(KWHC(-2))	-0.18027	0.092936	-1.939713	0.0653
DLOG(PNG)	-0.005509	0.020651	-0.266774	0.7921
DLOG(PNG(-1))	-0.037541	0.020714	-1.81232	0.0836
DLOG(HDD)	0.023121	0.062335	0.370908	0.7143
DLOG(HDD(-1))	-0.046833	0.071372	-0.656191	0.5185
DLOG(HDD(-2))	0.048406	0.063913	0.757372	0.4569
DLOG(CDD)	0.114898	0.047397	2.424138	0.024
CointEq(-1)*	-0.981938	0.107441	-9.139331	0

Diagnostic statistics for the underlying ARDL model:

R-squared	0.850446	Mean dependent var	0.003543
Adjusted R-squared	0.800595	S.D. dependent var	0.061452
S.E. of regression	0.027441	Akaike info criterion	-4.128075
Sum squared resid	0.020332	Schwarz criterion	-3.692691
Log likelihood	86.36938	Hannan-Quinn criter.	-3.974582
F-statistic	17.05966	Durbin-Watson stat	1.632327
Prob(F-statistic)	0		

Table 13: Alternative Long-Run ARDL Specification 3: ARDL(3,0,0,0,1,0) using SIC

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(PE)	0.160681	0.145193	1.106671	0.2782
LOG(PNG)	-0.031049	0.024428	-1.271043	0.2146
LOG(YCAP)	0.592513	0.115492	5.130316	0
LOG(HDD)	0.11276	0.114568	0.984225	0.3337
LOG(CDD)	0.140267	0.081364	1.723957	0.0961

Diagnostic statistics for the underlying ARDL model:

R-squared	0.923654	Mean dependent var	8.872221
Adjusted R-squared	0.898206	S.D. dependent var	0.093826
S.E. of regression	0.029935	Akaike info criterion	-3.9541
Sum squared resid	0.024195	Schwarz criterion	-3.518717
Log likelihood	83.15085	Hannan-Quinn criter.	-3.800607
F-statistic	36.29503	Durbin-Watson stat	1.78893
Prob(F-statistic)	0		

Table 14: ARDL Bounds Test for ARDL(3,0,0,0,1,0)

Bounds test results:			I(0)	I(1)
F-statistic	12.27169	10%	2.26	3.35
k	5	5%	2.62	3.79
		2.50%	2.96	4.18
		1%	3.41	4.68

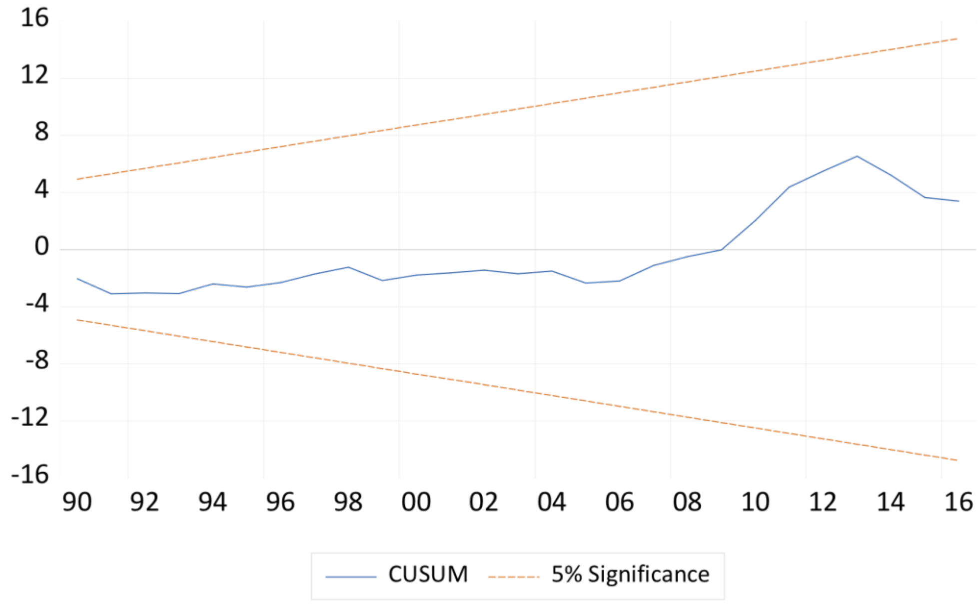

Figure 7: CUSUM for ARDL(3,0,0,0,1,0) (SIC)

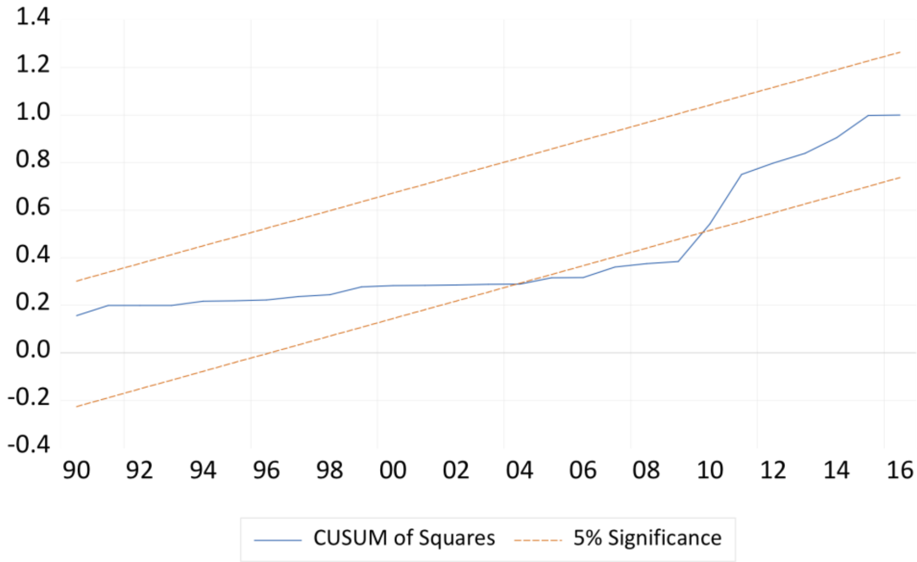

Figure 8: CUSUMSQ for ARDL(3,0,0,0,1,0) (SIC)

Table 12: Error Correction Model for ARDL(3,0,0,0,1,0) using SIC

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.99769	0.534528	9.349731	0
DLOG(KWHC(-1))	-0.420963	0.09194	-4.578665	0.0001
DLOG(KWHC(-2))	-0.195518	0.089815	-2.176892	0.0384
DLOG(HDD)	0.045741	0.051867	0.881896	0.3856
CointEq(-1)*	-0.931269	0.099691	-9.341593	0

Diagnostic statistics for the underlying ARDL model:

R-squared	0.822027	Mean dependent var	0.003543
Adjusted R-squared	0.79978	S.D. dependent var	0.061452
S.E. of regression	0.027497	Akaike info criterion	-4.22437
Sum squared resid	0.024195	Schwarz criterion	-4.006679
Log likelihood	83.15085	Hannan-Quinn criter.	-4.147624
F-statistic	36.95067	Durbin-Watson stat	1.78893
Prob(F-statistic)	0		

Vita

Felipe Francisco Mejia grew up in Boulder, Colorado and moved to El Paso, Texas in 2007. He enrolled at the University of Texas at El Paso in 2010 and graduated with summa cum laude honors receiving the Bachelor in Business Administration in Economics degree in 2014. As an undergraduate, he accepted an internship with the Economic Research Department at El Paso Electric Company. He accepted a graduate internship with El Paso Electric after enrolling in the Master of Science in Economics program. While in the M.S. Economics program, he accepted an offer as a Real-Time Energy Trader for El Paso Electric in the Power Marketing Department.

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This thesis was typed by Felipe Mejia.