

Metropolitan Evidence Regarding Small Commercial and Industrial Electricity Consumption

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ABSTRACT

Small commercial and industrial (CIS) electricity demand is an important category of electric energy consumption. Historically, it has received substantially less research attention than residential usage, potentially due to data constraints. This study seeks to partially fill that gap in the energy economics literature by employing a fairly unique data set for the El Paso, Texas, USA metropolitan economy that includes private capital stock estimates from 1978 through 2017. The empirical model is specified using a recently developed analytical framework based on duality theory and a derived input demand function. Parameter estimation is completed using an Autoregressive-distributed lag model and an error correction model. In the long-run, CIS customers in El Paso respond only to own-price and the quantity of capital stock per capita. In the short-run, CIS customers adjust their electricity usage in response to changes in all variables except for the price of electricity. The most unexpected result from this analysis is a short-run income elasticity of -0.32 , indicating that CIS electricity usage decreases with economic expansion in El Paso, Texas.

Keywords: Electricity Usage, Metropolitan Economic Growth, Small Commercial and Industrial Customers, Capital Stocks, Duality Theory, Derived Input Demand

JEL Classifications: Q41, R11, M21

1. INTRODUCTION

This study analyzes the usage of electricity as an input in production by small commercial and industrial (CIS) customers in El Paso, Texas from 1978 to 2017. Explanatory variables include an average price of electricity, an average natural gas price, labor, per capita personal income, private capital stock per capita, and weather variables. Parameter estimation techniques employed include an autoregressive-distributed lag model (ARDL) and an error correction model (ECM).

It is helpful for regional utilities and regulatory agencies to understand how changes in economic conditions affect small industrial and commercial electricity consumption. If usage increases with income growth, generation capacity may need to be expanded (Fullerton et al., 2012; Bildirici, 2013). However, if

usage decreases with increases in income within this rate class, pressures to increase generation capacity will be less severe (Fullerton et al., 2016).

El Paso Electric Company (EPEC) is an investor owned regulated, public utility that has a service territory of 10,000 square miles, stretching from Hatch, New Mexico to Van Horn, Texas, and includes two cross-border transmission connections to Ciudad Juárez, Mexico (EPEC, 2017a). EPEC energy sources include nuclear, natural gas, purchased power, and solar. The electricity company owns six generation facilities and has a net dependable generating capacity of approximately 2082 MW (EPEC, 2017a).

EPEC is a summer-peaking utility. In 2017, EPEC had 417,900 retail customers. The average number of small industrial and commercial (CIS) customers in 2017 was 41,978. Total CIS usage

during this period was approximately 2411 MWH of the total 7844 MWH (megawatt-hours) retail sales in 2017 (EPEC, 2017a). In other words, CIS customers represented 10% of EPEC retail accounts in 2017, and CIS usage accounted for about 31% of total retail MWH sales for EPEC that year (EPEC, 2017a).

Section two provides a brief overview of related literature. The third sections describes the model specification. Section four reviews the data employed for this study. Estimation results are summarized in the fifth section. The study concludes with result implications and suggestions for future research.

2. LITERATURE REVIEW

Most prior research indicates that commercial and industrial electricity usage increases as income, output, value-added, or economic activity increase (Houthakker, 1951; Baxter and Rees, 1968; Hawkins, 1975; Taylor, 1975; Polemis, 2007; Madlener et al., 2011; Cebula, 2013; Lim et al., 2014; Bildirici and Kayikci, 2016). Long-run elasticities are also larger, in absolute magnitude, than short-run elasticities. Estimated long-run income elasticities range from 0.60 to 1.67, while short-run income elasticities range from 0.11 to 0.82 for the commercial and industrial rate classes across numerous studies (Mount et al., 1973; Murray et al., 1978; Fatai et al., 2003; De Vita et al., 2006; Polemis, 2007; Amusa et al., 2009; Madlener et al., 2011; Lim et al., 2014; Kohler, 2014; Burke and Abayasekara, 2018).

A variety of studies indicate that long-run changes in economic activity or personal income are important in explaining variations in commercial and industrial electricity demand, short-run income changes are statistically insignificant or irrelevant (Zachariadis and Pashourtidou, 2007; Amusa et al., 2009). Eltony and Hajeesh (1999) model electricity demand in the commercial sector of Kuwait, with income proxied by real GDP. Results suggest commercial electricity demand does not respond to changes in income in the short-run, but usage is more responsive in the long-run, due to capital stock adjustments. Some studies find inverse relationships between commercial and industrial electricity usage and income. Watson et al. (1987) forecast short-run commercial electricity sales in Massachusetts and Rhode Island. Regional economic activity is proxied by unemployment. Surprisingly, the unemployment rate coefficient is -0.31 , implying that the commercial sector treats electricity as an inferior good in this region.

The price, or own-price, of electricity is also an important explanatory variable for commercial and industrial electricity consumption. Most analyses report negative own-price coefficients, with electricity consumption decreasing as price increases in the short-run and in the long-run (Mount et al., 1973; Murray et al., 1978; Chung and Aigner, 1981; Fatai et al., 2003; De Vita et al., 2006; Polemis, 2007; Madlener et al., 2011; Cebula, 2013; Lim et al., 2014; Kohler, 2014). Conversely, results of some studies suggest that commercial and industrial electricity demands are unresponsive to price changes in the long-run and/or the short-run (Baxter and Rees, 1968; Hawkins, 1975, Amusa et al., 2009). Commercial sector electricity consumption has also been found to be unresponsive to short-run prices changes, but extremely price

elastic in the long-run (Eltony and Hajeesh, 1999; Zachariadis and Pashourtidou, 2007). Bildirici and Kayikci (2016) find negative price elasticities in the short-run, but, surprisingly, positive long-run elasticities for countries in Eastern Europe.

As with analyses of residential electricity usage, a long-standing debate exists over to how to measure the price of electricity. Fisher and Kaysen (1962) argue that average prices and marginal prices are both adequate because of marginal price heterogeneity among electric utilities. Additionally, because of historical marginal price data limitations, many research studies often use average price variables (Halvorsen, 1978; Shin, 1985). Watson et al. (1987) notes that firm demand for electricity changes little in response to short-run changes in price, and, therefore, includes an average price measure to proxy long-run, trend movements in commercial electricity demand. Furthermore, because the CIS customer class within EPEC is charged a standard service monthly flat rate of \$0.11034 per kWh in the summer and \$0.10034 per kWh in the winter (EPEC, 2017b), there is no distinction between marginal and average price (Denton, et al., 2003). Amusa et al. (2009) justify the use of average electricity prices because customers react to the full costs of electricity rather than components of electricity costs. Finally, average price variables have also been found to yield reliable results in prior studies of electricity consumption in El Paso (Fullerton, 1998; Fullerton et al., 2016).

Another variable that often helps model commercial and industrial electricity consumption is the price of substitute fuels. Murray et al. (1978) obtains a positive cross-price elasticity coefficient, suggesting oil and electricity are substitutes in Virginia. Fatai et al. (2003) use an index of substitute prices and find long-run and short-run cross-price elasticities of 0.35 and 0.25, respectively. However, Baxter and Rees (1968) conclude that industrial electricity demand is relatively unresponsive to substitute fuel prices. Hawkins (1975) also finds that commercial and industrial demand for electricity is insensitive to substitute price changes in New South Wales, Australia. De Vita et al. (2006) discovers that diesel and kerosene substitute prices are insignificant because of the limited ability to switch between grid electricity and auto-generators in Namibia.

Weather variables are also widely used in econometric models of electricity consumption (Murray et al., 1978; Cebula, 2013). Watson et al. (1987) uses cooling-degree days (CDD), heating-degree days (HDD), and monthly dummy variables to capture the effects of weather on electricity sales. One additional CDD increases electricity sales to the commercial rate class by 26,284 kWh per customer per year, and an additional HDD increases sales to the commercial rate class by 7467 kWh per customer per year. Fatai et al. (2003) concludes that a 1% HDD increase will increase total electricity consumption by 33% in New Zealand. Highlighting the potentially important role of climate on CIS sales in summer peaking regions, Zachariadis and Pashourtidou (2007) finds the commercial sector is more responsive to short-term variations caused by weather, than to changes in income and price in Cyprus.

Many studies also examine how commercial and industrial usage responds to deviations from equilibrium positions (Eltony and

Hajeeh, 1999; Kohler, 2014). A model or series reaches equilibrium position when it has no further tendency to change. Eltony and Hajeeh (1999) report error correction results that indicate very rapid commercial electricity demand disequilibria responses in Kuwait. Zachariadis and Pashourtidou (2007) observe that commercial electricity consumption reverts faster to equilibrium than does the residential sector in Cyprus. In contrast, Amusa et al. (2009) obtains an error correction coefficient of -0.13 , meaning that equilibrium re-attainment is relatively slow in South Africa. Results from Madlener et al. (2011) indicate that convergence to a new long-run equilibrium can require between 3 and 14 years depending on the industrial sector in Germany. Bildirici and Kayikci (2016) also documents very slow rates of convergence to equilibrium in Eastern European countries, with error correction terms that range from -0.01 to -0.08 .

Numerous studies on commercial and industrial electricity demand use ECM within an ARDL framework (Fatai et al., 2003; Amusa et al., 2009; Kohler, 2014; Bildirici and Kayikci, 2016). ARDL models can correct for endogeneity and are straightforward and simple to use. The bounds testing approach to cointegration within an ARDL framework can estimate both long-run and short-run elasticities, even when the variables are of $I(0)$ and $I(1)$ mixed order of integration (Pesaran and Shin, 1999; Dergiades and Tsoulfidis, 2008; 2011). Table 1 summarizes the elasticity coefficients from this branch of the literature. Commercial and industrial long-run income elasticities range from 0.60 to 1.67, while short-run income elasticities range from 0.11 to 0.82. Except for the study by Bildirici and Kayikci (2016), long-run price elasticities range from -0.21 to -1.36 , while short-run price elasticities range from -0.04 to -0.63 . Not surprisingly, business electricity demand is relatively more inelastic in the short-run than in the long-run.

This effort investigates CIS electricity usage in El Paso, Texas. With more than 840,000 residents and more than 10,800 commercial establishments, El Paso is one of the largest metropolitan economies in Texas (Fullerton et al., 2018). A recent empirical study examines the responsiveness of residential electricity usage

in El Paso, Texas to changes in electricity prices, natural gas prices, per capita income, housing stocks, HDD, and CDD (Fullerton et al., 2016). Results indicate that, over the long-run, El Paso households consume electricity as an inferior good and in a manner that is price elastic. The formal model specification for CIS usage is based upon duality theory using the analytical framework of Allen and Fullerton (2018). In that construct, CIS usage is characterized by an input-demand function that is derived from a normalized quadratic profit function. Parameter estimation for the resulting expression is discharged within an ARDL framework.

3. EMPIRICAL MODEL AND DATA

3.1. Empirical Model

Duality theory and a normalized quadratic functional form are used to describe CIS demand for electricity as derived demand (Allen and Fullerton, 2018). The derived input-demand function for electricity shown in equation 1 is used to empirically specify and estimate long-run and short-run models of CIS electricity consumption using an ECM within an ARDL framework. ARDL estimation allows analyzing both short-run and long-run dynamics. That is helpful because of shortcomings that may arise within the context of static modeling approaches (Fox and Kivanda, 1994). This study employs time series data and the decisions of CIS firms are likely to be better modeled within dynamic frameworks (Clark and Grant, 2000; Boonsaeng and Wohlgenant, 2006). Additionally, the data-based approach is able to account for dynamic variations in CIS electricity demand over time, as it allows sample information to select the underlying data-generating process and capture the long-run equilibrium structure (Reziti and Ozanne, 1999).

$$-\frac{\partial \Pi (P_i; Z_K)}{\partial P_E} = X_E^* = \beta_E + \beta_{EE}P_E + \beta_{QE}P_Q + \beta_{EG}P_G + \beta_{EL}P_L + \beta_{EK}Z_K \tag{1}$$

Specifying the input-demand for electricity in an ARDL framework yields equation 2, where t is a time period subscript and k is the

Table 1: Summary of elasticity coefficients of the related literature

Author (s), year	Long-run equation		Short-run equation		
	Income	Price	Income	Price	Error correction term
Mount et al. (1973)	0.86	-1.36	0.11	-0.17	-
Murray et al. (1978), commercial	0.70	-0.47	-	-0.04	-
Murray et al. (1978), industrial	1.11	-0.21	0.82	-0.29	-
Eltony and Hajeeh (1999)	0.81	-0.98	0.34	-0.33	-1.10
Fatai et al. (2003)	0.70	-0.43	0.24	-0.18	-
De Vita et al. (2006)	0.59	-0.30	-	-	-
Zachariadis and Pashourtidou (2007)	1.12	-0.30	-	-	-0.23
Polemis (2007)	0.85	-0.85	0.61	-0.35	-0.24
Amusa et al. (2009)	1.67	-	-	-	-0.13
Madlener et al. (2011), industrial averages	1.14	-0.37	0.58	-0.44	-0.45
Kohler (2014)	0.63	-0.94	0.42	-0.63	-0.67
Lim et al. (2014)	1.09	-1.00	0.86	-0.42	-
Bildirici and Kayikci (2016), averages	0.71	1.59	0.37	-0.17	-0.07
Burke and Abayasekara (2018), commercial between panel IV estimates	0.59	-0.56	0.14 (total)	-0.09 (total)	-
Burke and Abayasekara (2018), industrial between panel IV estimates	-	-1.34	-	-	-

Coefficient results are for commercial, industrial, or aggregate usage. Empty cells indicate the coefficient was insignificant or not reported

number of lagged periods. Because the data are logarithmically transformed, the parameters represent elasticities of demand. C_t is CIS input demand for electricity, while PQ_t is normalized output price and PE_t , PG_t , and PL_t are normalized input-prices of electricity, natural gas, and labor, respectively. K_t is the fixed quantity of capital. The parameters, CDD_t and HDD_t , are CDD and HDD days and are used to measure how weather variations affect CIS electricity consumption. The random error term is denoted u_t . Once the long-run specification is developed, the next step is to ensure that no series within equation 2 is integrated of order 2 or higher. Series that are integrated of order 2 or higher require at least second-differencing to reach stationarity and are not suitable for ARDL estimation. An augmented dickey-fuller (ADF) unit root test is applied to the first difference of each series to examine if that is the case (Asteriou and Hall, 2015).

$$\ln C_t = \alpha_0 + \alpha_1 \ln C_{t-k} + \alpha_2 \ln PE_{t-k} + \alpha_3 \ln PQ_{t-k} + \alpha_4 \ln PG_{t-k} + \alpha_5 \ln PL_{t-k} + \alpha_6 \ln K_{t-k} + \alpha_7 \ln CDD_{t-k} + \alpha_8 \ln HDD_{t-k} + u_t \quad (2)$$

Next, the long-run cointegrating equation is specified and estimated. Specifying the input-demand function for electricity as a long-run cointegrating equation results is shown in equation 3, where Δ is the difference operator and v_t is a random error term. The coefficients β_1 through β_8 are short-run parameters, while the coefficients β_9 through β_{16} represent long-run parameters.

$$\Delta \ln C_t = \beta_0 + \beta_1 \Delta \ln C_{t-k} + \beta_2 \Delta \ln PE_{t-k} + \beta_3 \Delta \ln PQ_{t-k} + \beta_4 \Delta \ln PG_{t-k} + \beta_5 \Delta \ln PL_{t-k} + \beta_6 \Delta \ln K_{t-k} + \beta_7 \Delta \ln CDD_{t-k} + \beta_8 \Delta \ln HDD_{t-k} + \beta_9 \Delta \ln C_{t-1} + \beta_{10} \Delta \ln PE_{t-1} + \beta_{11} \Delta \ln PQ_{t-1} + \beta_{12} \Delta \ln PG_{t-1} + \beta_{13} \Delta \ln PL_{t-1} + \beta_{14} \Delta \ln K_{t-1} + \beta_{15} \Delta \ln CDD_{t-1} + \beta_{16} \Delta \ln HDD_{t-1} + v_t \quad (3)$$

Once equation 3 has been specified and estimated, a bounds test for cointegration is conducted to determine whether the variables exhibit a meaningful, long-run relationship (Pesaran and Shin, 1999; Nkoro and Uko, 2016). The advantages of the bound tests are two-fold. First, the bound test can be used whether the explanatory variables are I(0) or I(1). Second, the test can be used in cases involving small sample sizes (Pesaran et al., 2001).

The bounds test is an F-test of the null hypothesis, $H_0 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = 0$ against the alternative that H_0 is false (Pesaran et al., 2001). The computed F-statistic is then compared against two critical values for the opposing cases that all variables are I(0) or all variables are I(1). If the F-statistic falls between the upper and lower bounds, the test is deemed inconclusive. If the F-statistic is below the lower critical value, the null hypothesis cannot be rejected, therefore, cointegration does not exist. In contrast, if the F-statistic is above the upper critical value, the null hypothesis is rejected and cointegration does exist. Narayan (2005) offers critical values for cases of finite sample sizes ranging from $n = 30$ to $n = 80$ in increments of 5. Once the bounds test confirms the existence of a cointegrating relationship, the next step is to select the optimal number of lags for each variable, using the Schwarz Information Criterion (Asteriou and Hall, 2015).

After estimating the long-run cointegrating equation, the short-run ECM is specified and estimated. The short-run ECM derived from the ARDL model is shown in equation 4. The short-run ECM examines short-run departures from equilibrium. The

dependent variable is the first-differenced, natural logarithm of input quantity of electricity, denoted $\Delta \ln C_t$. The first-differenced, natural logarithm of the normalized output price is $\Delta \ln PQ_{t-k}$. The first-differenced, natural logarithms of the normalized input prices are $\Delta \ln PE_{t-k}$, $\Delta \ln PG_{t-k}$ and $\Delta \ln PL_{t-k}$. The first-differenced, natural logarithm of the fixed quantity of capital is $\Delta \ln K_{t-k}$. The first-differenced, natural logarithms of CDD and HDD are $\Delta \ln CDD_{t-k}$ and $\Delta \ln HDD_{t-k}$, respectively.

The error correction term, u_{t-1} , is the prior period disturbance term taken from the cointegrating equation. The sign of the coefficient of the error correction term is expected to lie between -1 and 0, as deviations from equilibrium will be offset by adjustments in the subsequent period (Fullerton et al., 2012; Asteriou and Hall, 2015). The magnitude of c_9 represents the speed of adjustment for re-attaining equilibrium. The reciprocal of c_9 represents the total amount of time required for complete error dissipation. The ARDL and ECM models are estimated using least squares analysis.

$$\Delta \ln C_t = c_0 + c_1 \Delta \ln C_{t-k} + c_2 \Delta \ln PE_{t-k} + c_3 \Delta \ln PQ_{t-k} + c_4 \Delta \ln PG_{t-k} + c_5 \Delta \ln PL_{t-k} + c_6 \Delta \ln K_{t-k} + c_7 \Delta \ln CDD_{t-k} + c_8 \Delta \ln HDD_{t-k} + c_9 u_{t-1} + w_t \quad (4)$$

Finally, the parameter stability in the ARDL model is examined using the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) tests (Brown et al., 1975; Garbade, 1975). These tests identify structural breakpoints within time series data. The null hypothesis of parameter constancy is $H_0: \beta_1 = \beta_2 = \dots = \beta_{16} = \beta$ and $\sigma_1^2 = \sigma_2^2 = \dots = \sigma_{16}^2 = \sigma^2$, where β is a vector of coefficients and σ^2 is the variance of the disturbance term across different sub-samples. Assuming the null is not rejected, b_{it} is obtained recursively and is the least-squares estimate of β_{it} , such that $b_{it-1} = (X_{it}' X_{it})^{-1} X_{it}' C_t$ where C_t is the dependent variable and X_{it} is a vector of independent variables. The recursive residual is defined as $w_i = \frac{c_t - x_{it}' b_{it-1}}{\sqrt{1 + x_{it}' (X_{it-1}' X_{it-1})^{-1} x_{it}}}$ with a mean of 0 and variance σ^2 (Tanizaki, 1995).

The CUSUM test statistic using the recursive residuals from Brown, et al. (1975) is $W_t = \frac{\sum_{i=k+1}^t w_i}{\hat{\sigma}_w}$, where $\hat{\sigma}_w^2 = \frac{\sum_{i=k+1}^n w_i^2}{n-k}$ (Tanizaki, 1995). Similarly, the CUSUMSQ test statistic uses the squared recursive residuals and defined as $S_t = \frac{\sum_{i=k+1}^t \hat{w}_i^2}{\sum_{i=k+1}^n \hat{w}_i^2}$ (Brown et al., 1975). If the computed test statistics remain within the critical-value boundaries, the null hypothesis cannot be rejected, and it is concluded that the data series are stable across time (Garbade, 1975).

3.2. Data

The dependent variable in this paper is CIS electricity consumption in kilowatt-hours per CIS customer billed by EPEC. The own-price

variable is average revenue per kilowatt-hour. Data for electricity consumption, the number of customers, and revenue are from El Paso Electric Company filings (EPEC, 2017c) with the Federal Energy Regulatory Commission. Annual frequency data from 1978 to 2017 are employed for this study.

El Paso per capita personal income is from the University of Texas at El Paso Border Region Modeling Project (Fullerton et al., 2018). The price of natural gas per CCF sold to Texas commercial consumers is used to estimate potential substitution or complementary effects between natural gas and electricity. This series was obtained from the United States Energy Information Administration (EIA, 2017). The price of labor is measured by El Paso wages and salaries paid per worker as reported by the Border Region Modeling Project (Fullerton et al., 2018). The quantity of capital is defined as the stock of El Paso private capital and is from the El Paso Central Appraisal District (EPCAD, 2017). CDD and HDD are defined as the number of degrees that the average temperature is either above or below 65° Fahrenheit during a 24-h period. Both series are compiled from the website of the National Oceanic and Atmospheric Administration Northeast Regional Climate Center (NOAA, 2017).

El Paso per capita personal income is deflated to real 2009 dollars using the personal consumption expenditures implicit price deflator. All other price and salary data are deflated using the U.S. GDP implicit price deflator (DEF) and are in real 2009 dollars. Both deflators are from the U.S. Bureau of Economic Analysis (BEA, 2017). The names, definitions, and units of measurement of all variables in the sample are listed in Table 2. Table 3 reports summary statistics for each data series.

4. EMPIRICAL RESULTS

Prior to parameter estimation, unit root tests are performed to ensure that no series is greater than I(2). The unit root test using the ADF test statistic indicates that all the variables included in the model are either I(0) or I(1) as shown in Table 4. These results indicate that the data are appropriate for analysis within an ARDL framework.

Degree of freedom constraints impose a maximum of four lags of the dependent variable and three lags of each explanatory variable in the ARDL equation specification. The model for per customer electricity consumption selected using the Schwarz Information Criterion is ARDL(3, 1, 3, 3, 3, 1, 2, 2). Parameter estimates and diagnostic statistics for the resulting ARDL model are shown in Table 5.

A Breusch-Godfrey serial correlation LM test of the null hypothesis that the residuals are not autocorrelated indicates that serial correlation is not problematic at 2 lags. The Breusch-Pagan-Godfrey Heteroscedasticity Test for the null hypothesis that the residuals are homoscedastic also indicates that the error term variance is constant in this model. The results of both tests are reported in Tables 6 and 7.

The computed F-statistic for the null hypothesis $H_0: \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = \beta_{16} = 0$ is 6.93 as shown in Table 8. This is higher than

Table 2: Variables

Variable	Definition
<i>C</i>	CIS electricity consumption in kilowatt-hours per CIS customer billed by EPEC, obtained from EPEC Federal Energy Regulatory Commission Form No. 1., annual report of major electric utilities, licensees, and others
<i>CUST</i>	Average number of CIS customers billed by EPEC, obtained from EPEC Federal Energy Regulatory Commission Form No. 1., annual report of major electric utilities, licensees, and others
<i>PE</i>	Real EPEC average price per kilowatt-hour of electricity in U.S. cents, base period 2009=1, obtained from EPEC Federal Energy Regulatory Commission Form No. 1., annual report of major electric utilities, licensees, and others
<i>PQ</i>	Real El Paso Personal Income per capita in U.S. dollars, base period 2009=1, obtained from the UTEP border region modeling project
<i>PG</i>	Real price per CCF of natural gas sold to Texas commercial consumers in U.S. dollars, base period 2009=1, obtained from the U.S. energy information administration
<i>PL</i>	Real El Paso wages and salaries paid per worker in U.S. dollars, base period 2009=1, obtained from the UTEP border region modeling project
<i>K</i>	Quantity of real El Paso private capital stock per capita in U.S. dollars, base period 2009=1, obtained from El Paso central appraisal district
<i>CDD</i>	El Paso cooling degree days, obtained from national oceanic and atmospheric administration northeast regional climate center
<i>HDD</i>	El Paso heating degree days, obtained from national oceanic and atmospheric administration northeast regional climate center
<i>DEF</i>	U.S. gross domestic product implicit price deflator, base period 2009=1, obtained from U.S. bureau of Economic analysis
<i>PCE</i>	Personal consumption expenditures implicit price deflator, base period 2009=1, obtained from U.S. bureau of economic analysis
<i>POP</i>	El Paso population, obtained from the UTEP border region modeling project

Table 3: Data summary statistics

Variable name	C	PE	PQ	PG
Mean	65,715	12.09	22,117	7.32
Max.	73,211	16.22	31,337	11.38
Min.	57,428	9.29	15,684	5.41
Variance	21,953,910	2.79	20,496,672	2.70
Standard deviation	4,686	1.67	4,527	1.64
Skewness	0.13	0.75	0.33	1.03
Kurtosis	1.74	3.51	1.90	3.16
Coefficient of variation	0.07	0.14	0.20	0.22
Variable name	PL	K	CDD	HDD
Mean	25,474	6,697	2,463	2,366
Max.	28,354	10,876	3,141	3,012
Min.	23,000	4,738	1,816	1,522
Variance	3,285,319	3,185,640	105,195	99,460
Standard deviation	1813	1785	324	315
Skewness	0.16	0.93	-0.12	-0.18
Kurtosis	1.55	2.56	2.53	3.11
Coefficient of variation	0.07	0.27	0.13	0.13

the 5% critical value for the upper bound computed by Narayan (2005). The bounds test results in Table 8 indicate that the variables included in the model are cointegrated. Further diagnostic checks, the CUSUM and CUSUMSQ tests of parameter stability, are also carried out. Figures 1 and 2 confirm that the model parameters are relatively stable over time and the computed statistics do not surpass the 5% critical bounds.

Estimation results for the long-run Cointegrating and the long-run level models are shown in Tables 9 and 10, respectively. The majority of the estimates are not statistically significant in Table 10, indicating long-run independence. Only the long-run own-price and capital stock coefficient estimates from the cointegrating equation are statistically significant at the 5% level.

Table 4: Unit root test results

Series	Augmented dickey-fuller test statistic	Prob.*
D (LC)	-3.094213	0.036
D (LPE)	-4.463706	0.001
D (LPQ)	-9.145892	0.000
D (LPG)	-6.498174	0.000
D (LPL)	-5.776990	0.000
D (LK)	-6.004136	0.000
D (LCDD)	-9.207738	0.000
D (LHDD)	-8.566317	0.000

*MacKinnon (1996) one-sided P values

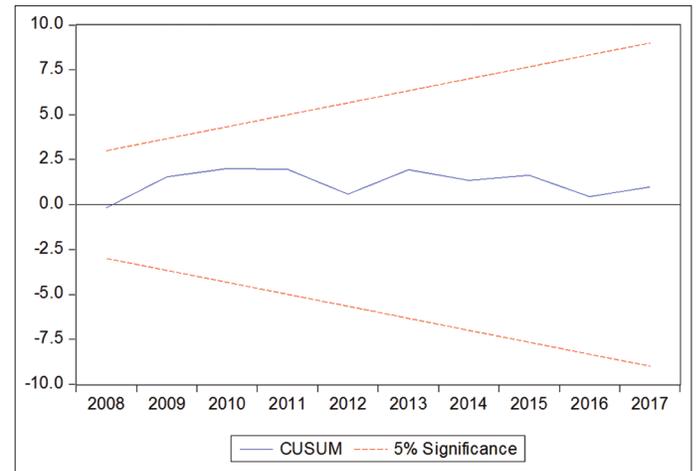
Table 5: ARDL model

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LC(-1)	0.281660	0.221141	1.273667	0.2290
LC(-2)	0.101338	0.222043	0.456390	0.6570
LC(-3)	0.224660	0.177347	1.266781	0.2314
LPE	-0.030481	0.058230	-0.523460	0.6110
LPE(-1)	-0.219490	0.062730	-3.498950	0.0050
LPQ	-0.322989	0.159628	-2.023383	0.0680
LPQ(-1)	0.304113	0.147006	2.068720	0.0629
LPQ(-2)	-0.245984	0.132249	-1.860005	0.0898
LPQ(-3)	0.360593	0.122189	2.951107	0.0132
LPG	-0.118590	0.033925	-3.495594	0.0050
LPG(-1)	0.064749	0.023971	2.701195	0.0206
LPG(-2)	0.003730	0.017858	0.208872	0.8384
LPG(-3)	0.048792	0.018975	2.571437	0.0260
LPL	0.372276	0.226078	1.646669	0.1279
LPL(-1)	-0.220639	0.242221	-0.910900	0.3819
LPL(-2)	0.743197	0.248157	2.994872	0.0122
LPL(-3)	-0.511704	0.221569	-2.309453	0.0413
LK	-0.315899	0.106071	-2.978177	0.0126
LK(-1)	-0.162131	0.123295	-1.314984	0.2153
LCDD	0.107399	0.024060	4.463791	0.0010
LCDD(-1)	-0.006755	0.021032	-0.321185	0.7541
LCDD(-2)	-0.054652	0.024085	-2.269178	0.0444
LHDD	-0.025861	0.026016	-0.994062	0.3416
LHDD(-1)	-0.017290	0.022395	-0.772019	0.4564
LHDD(-2)	-0.066661	0.024897	-2.677418	0.0215
c	6.163650	4.571040	1.348413	0.2046
R-squared	0.996395	Mean dependent var	11.09666	
Adjusted R-squared	0.988202	S.D. dependent var	0.070582	
S.E. of regression	0.007666	Akaike info criterion	-6.711536	
Sum squared resid	0.000647	Schwarz criterion	-5.579539	
Log likelihood	150.1634	Hannan-Quinn criter.	-6.312454	
F-statistic	121.6173	Durbin-Watson stat	2.750275	
Prob (F-statistic)			0.000000	

*P-values and any subsequent tests do not account for model selection

The own-price elasticity coefficient is negative as hypothesized sign and falls within the inelastic range. That suggests that changes in the average price of electricity have, historically, induced relatively small effects on the quantity of the electricity demanded by El Paso CIS customers over the long-run. Other things equal, a 1% increase in the real average price of electricity is associated with a 0.64% decrease in usage per CIS customer over the long-run, a value that is almost half as small as what has been documented

Figure 1: Cumulative sum results for electricity consumption per customer



for residential customers in this metropolitan economy (Fullerton et al., 2016). Other studies have also obtained long-run own-price elasticities for the commercial customer class that are <1.0 in absolute value (Fatai et al. 2003; De Vita et al., 2006; Zachariadis and Pashourtidou, 2007; Polemis, 2007; Ros, 2017).

The long-run coefficients for LPG, LPQ, and LPL have large standard errors and are statistically insignificant in Table 10. The statistical insignificance of the price of natural gas coefficient, LPG, is not completely surprising, as natural gas is a relatively costly substitute for electricity in the long-run (Bernstein and Griffin, 2006). While there have been some recent substitutions of natural gas for electricity in heating processes, heating requirements are not particularly demanding in the desert climate of El Paso, Texas. By comparison, Burke and Abayasekara (2018) also finds that the price of natural gas does not help explain variations in commercial electricity consumption in the long-run in the United States at the state level.

The insignificance of the economic activity parameter estimate implies that CIS electricity demand does not respond in a

Figure 2: Cumulative sum of squares results for electricity consumption per customer

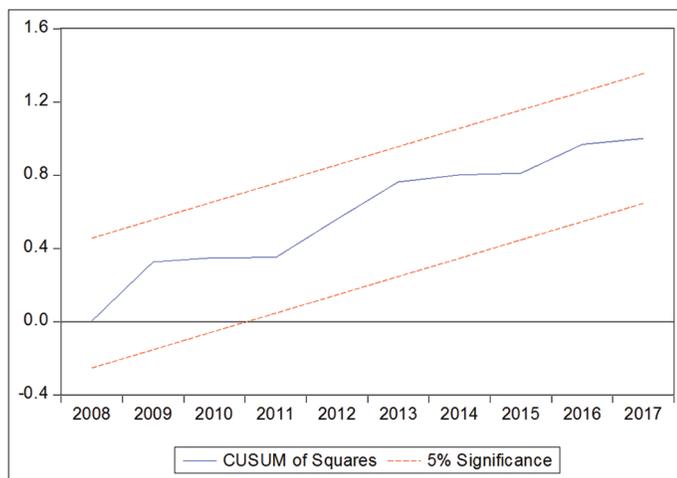


Table 6: Serial correlation test results

Breusch-Godfrey serial correlation LM test			
F-statistic	2.487594	Prob. F (2,9)	0.1380

Table 7: Heteroskedasticity test results

Heteroskedasticity test: Breusch-Pagan-Godfrey			
F-statistic	0.853788	Prob. F (25,11)	0.6459

Table 8: ARDL bounds test

Test statistic	Value	k
F-statistic	6.925392	7
Critical value bounds		
Significance	I (0) Bound	I (1) Bound
10%	2.03	3.13
5%	2.32	3.50
2.5%	2.60	3.84
1%	2.96	4.26

statistically reliable manner to economic expansion or contraction in El Paso. This is possibly a consequence of energy-efficiency gains in the production activities of final goods and services in both small commerce and industry. This result is out of step with strong relationships between output and non-residential usage in many other studies (Houthakker, 1951; Baxter and Rees, 1968; Hawkins, 1975; Taylor, 1975; Polemis, 2007; Madlener et al., 2011; Cebula, 2013; Lim et al., 2014; Bildirici and Kayikci, 2016; Burke and Abayasekara, 2018). For El Paso, the relationship appears positive, but less reliable than in other regions.

The large standard error for the price of labor coefficient suggests that it may be more feasible to use capital in place of labor over the course of the long-run by CIS firms in El Paso. That potentially results from the status of labor as the single largest cost of business for most firms in this sector. Barnett et al. (1998) found that three of the four industries included in an analysis of electricity usage in Alabama from 1979 to 1982 are biased away from labor. That study also indicates that improvements in technology lead to greater capital shares at the expense of labor in production processes. Greater reliance on automation in both industry and commerce has affected global demand for labor throughout history (Lucking-Reiley and Spulber, 2001).

The capital stock coefficient estimate in Table 10 indicates that a 1% increase in the quantity of real capital stock per capita is associated with a 1.22% decline in electricity consumption per CIS customer in El Paso over the long-run. That is not unexpected, as improved building designs (Ruparathna et al., 2016) and more efficient appliances (Garg et al., 2017) allow for reduced electricity usage in commercial sectors throughout the world. New investments by CIS businesses in El Paso undoubtedly take advantage of superior construction and appliance advances over the course of time.

Neither of the long-run CDD and HDD coefficients in Table 10 satisfy the 5% significance criterion. In the case of the CDD parameter, the relatively low t-statistic most likely indicates that the positive relationship between CIS electricity consumption and CDD is not always numerically reliable. That is somewhat surprising because hot weather is generally regarded as an important driver of electricity consumption in this region. The sign of the HDD coefficient implies that colder weather is associated with reduced electricity usage by CIS firms. Numerous factors may contribute to this outcome. Examples include weather patterns, technology, climate change, and latitude (Crowley and Joutz, 2005; Hor et al., 2005; Polemis, 2007; EIA, 2003; 2012; EPA, 2015). This result in Table 10 is not unique to El Paso. Burke and Abayasekara (2018) also document a long-run, inverse relationship between HDD and state-level commercial electricity demand across the United States.

The prior period error term from the long-run cointegrating model in Table 9 is taken and then added as a parameter to the ECM equation. The estimation results for the short-run ECM regression are reported in Table 11. As expected, the short-run elasticities are smaller in magnitude than the corresponding long-run elasticities. Those outcomes confirm patterns documented elsewhere that the

Table 9: Long-run cointegrating model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D (LC(-1))	-0.325998	0.183669	-1.774928	0.1036
D (LC(-2))	-0.224660	0.177347	-1.266781	0.2314
D (LPE)	-0.030481	0.058230	-0.523460	0.6110
D (LPQ)	-0.322989	0.159628	-2.023383	0.0680
D (LPQ(-1))	-0.114609	0.154359	-0.742482	0.4734
D (LPQ(-2))	-0.360593	0.122189	-2.951107	0.0132
D (LPG)	-0.118590	0.033925	-3.495594	0.0050
D (LPG(-1))	-0.052522	0.022056	-2.381348	0.0364
D (LPG(-2))	-0.048792	0.018975	-2.571437	0.0260
D (LPL)	0.372276	0.226078	1.646669	0.1279
D (LPL(-1))	-0.231493	0.248018	-0.933370	0.3707
D (LPL(-2))	0.511704	0.221569	2.309453	0.0413
D (LK)	-0.315899	0.106071	-2.978177	0.0126
D (LCDD)	0.107399	0.024060	4.463791	0.0010
D (LCDD(-1))	0.054652	0.024085	2.269178	0.0444
D (LHDD)	-0.025861	0.026016	-0.994062	0.3416
D (LHDD(-1))	0.066661	0.024897	2.677418	0.0215
LPE(-1)	-0.249972	0.079011	-3.163758	0.0090
LPQ(-1)	0.095734	0.191146	0.500841	0.6264
LPG(-1)	-0.001318	0.025280	-0.052134	0.9594
LPL(-1)	0.383130	0.302687	1.265764	0.2317
LK(-1)	-0.478030	0.149020	-3.207835	0.0083
LCDD(-1)	0.045992	0.038691	1.188676	0.2596
LHDD(-1)	-0.109812	0.051333	-2.139197	0.0557
LC(-1)	-0.392341	0.114512	-3.426201	0.0057
c	6.163650	4.571040	1.348413	0.2046
R-squared	0.932563	Mean dependent var		-0.001940
Adjusted R-squared	0.779296	S.D. dependent var		0.016319
S.E. of regression	0.007666	Akaike info criterion		-6.711536
Sum squared resid	0.000647	Schwarz criterion		-5.579539
Log likelihood	150.1634	Hannan-Quinn criter.		-6.312454
F-statistic	6.084579	Durbin-Watson stat		2.750275
Prob (F-statistic)		0.001673		

impacts of the explanatory variables on CIS electricity usage are more dramatic over the long-run (Burke and Abayasekara, 2018). The parameter coefficients in the ECM results that are statistically significant at the 5% level include lags of the dependent variable, personal income per capita, the price of natural gas, the price of labor, per capita capital stock, and the CDD and HDD weather variables.

The insignificant own-price elasticity coefficient in Table 11 indicates that CIS customers do not respond very reliably to short-run variations in the price of electricity. Similarly, Zachariadis and Pashourtidou (2007) and Amusa et al. (2009) also report price effects in the short-run are statistically indistinguishable from zero. A delayed response to electricity price changes is logical. CIS production activities are generally difficult to alter in the short-run because of capital requirements and it is easier to adjust factors over the long-run (Burke and Abayasekara, 2018).

The short-run cross-price elasticities for natural gas are negative in Table 11. That differs from earlier studies such as Murray et al. (1978) or Fatai et al. (2003), which obtain positive cross-price elasticity coefficients. This result indicates that El Paso CIS customers treat electricity and natural gas as complements in the short-run. This is reasonable, as electricity and natural gas are often used as joint inputs (Burke and Abayasekara, 2018). The negative natural gas price coefficient also stands in contrast

Table 10: Long-run coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LPE	-0.637127	0.198712	-3.206284	0.0084
LPQ	0.244006	0.436804	0.558617	0.5876
LPG	-0.003359	0.064380	-0.052177	0.9593
LPL	0.976521	0.839757	1.162862	0.2695
LK	-1.218403	0.097033	-12.556535	0.0000
LCDD	0.117223	0.099079	1.183124	0.2617
LHDD	-0.279888	0.140540	-1.991518	0.0718

to the findings of Fullerton et al. (2016), which discovers that residential customers in El Paso treat natural gas and electricity as substitutes. Holding all else constant, an increase in the price of natural gas by 1% will decrease the use of electricity per CIS customer by 0.22% within 3 years.

The statistically significant contemporaneous and second-lag coefficients of the price of labor are positive, suggesting that labor and electricity are substitutes in the short-run. As wages per worker increase by 1%, electricity demanded per CIS customer increases by 0.65% after 3 years. Hesse and Tarkka (1986) also reports evidence that labor and electricity are substitutes in the manufacturing industry in nine European countries from 1960 to 1980.

The capital stock per capita parameter estimate is negative in the short-run. El Paso CIS electricity consumption decreases by 0.32%

Table 11: Error correction model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D (LC(-1))	-0.325998	0.117770	-2.768096	0.0183
D (LC(-2))	-0.224660	0.093842	-2.394035	0.0356
D (LPE)	-0.030481	0.030367	-1.003751	0.3371
D (LPQ)	-0.322989	0.097592	-3.309569	0.0070
D (LPQ(-1))	-0.114609	0.089164	-1.285378	0.2251
D (LPQ(-2))	-0.360593	0.078768	-4.577906	0.0008
D (LPG)	-0.118590	0.015419	-7.690894	0.0000
D (LPG(-1))	-0.052522	0.010831	-4.849349	0.0005
D (LPG(-2))	-0.048792	0.009737	-5.010780	0.0004
D (LPL)	0.372276	0.130274	2.857625	0.0156
D (LPL(-1))	-0.231493	0.122097	-1.895980	0.0845
D (LPL(-2))	0.511704	0.129347	3.956051	0.0022
D (LK)	-0.315899	0.052529	-6.013802	0.0001
D (LCDD)	0.107399	0.013951	7.698165	0.0000
D (LCDD(-1))	0.054652	0.013346	4.095139	0.0018
D (LHDD)	-0.025861	0.012411	-2.083762	0.0613
D (LHDD(-1))	0.066661	0.013147	5.070487	0.0004
c	6.163650	0.646401	9.535329	0.0000
CointEq(-1)	-0.392341	0.041206	-9.521537	0.0000

in response to a 1% increase in the capital stock per capita. That implies that capital stock upgrades lead to short-run efficiency gains by commercial electricity users in El Paso. In contrast, Adebola and Opeyemi (2011) does not find a causal relationship between capital and electricity, while Hesse and Tarkka (1986) observes a positive relationship between capital and electricity in nine European countries from 1973 to 1980.

The signs of the CDD and HDD coefficients are positive as hypothesized. Subsequent to a 1% increase in CDD, CIS electricity demand per customer grows by 0.16% within 2 years of the temperature increment. A 1% increase in HDD leads CIS electricity usage to grow by 0.04% within 2 years. Watson et al. (1987), Fatai et al. (2003), and Zachariadis and Pashourtidou (2007) also document increased electricity consumption during periods of hotter and colder weather. The statistical significance of both sets of parameters underscores the reliability of these reactions to climate variations.

Among the most interesting results in Table 11, the signs of the personal income per capita coefficients are negative. An increase in El Paso real personal income per capita by 1% leads to a 0.80% decline in CIS electricity within a 3-year period. That runs counter to the service sector electricity demand outcomes obtained for Korea by Lim et al. (2014). CIS electricity consumption per customer has been declining since 2000, a large portion of the sample period. That may be due to more energy-efficient appliances and machinery becoming available to CIS businesses in El Paso subsequent to the turn of the century.

As hypothesized, the sign for the error correction parameter is less than zero. The statistically significant error term parameter in the Table 11 ECM equation indicates that approximately 39% of any deviation from equilibrium is corrected within 1 year. The magnitude of the error correction term is within the range of error correction terms reported by various other studies (Eltony and Hajeesh, 1999; Zachariadis and Pashourtidou, 2007; Amusa

et al.; 2009; Kohler; 2014). Approximately 2.5 years are required for complete long-run equilibrium re-attainment.

5. CONCLUSION

An ARDL approach is used to analyze CIS electricity consumption in El Paso, Texas. The theoretical model employs duality theory and derived input demand. Sample data collected for El Paso include fairly comprehensive information that allow specifying a reasonable facsimile of the analytical model. Among other things, ARDL modeling also allows for different optimal lag lengths. It also has reliable finite sample properties. Instead of a two-stage regression approach, the ARDL bounds testing technique employed specifies the equation in a single, reduced form, allowing for simultaneous estimation of short-run and long-run effects. The ARDL approach has also been found to produce smaller forecasting errors and superior forecasting performances over other dynamic model constructs.

Results obtained indicate that CIS electricity demand reacts to changes in own-price and the quantity of capital stock per capita in the long-run in El Paso. An inverse, long-run relationship between CIS electricity usage and the amount of capital stock is documented, potentially due to the emergence of more energy-efficient machinery. In the short-run, gas and electricity are used as complements, while labor and electricity are substitutes in the short-run. Short-run results further indicate that CIS customers in El Paso are not sensitive to own-price changes. The inverse relationship between the capital stock and electricity consumption holds in the short-run as well. Variations in CDD and HDD are found to affect short-run changes in electricity consumption within the CIS customer class. The error correction term indicates that CIS customers adjust to deviations from equilibrium at a somewhat moderate rate, with 39% of the correction occurring within 1 year and 100% of the correction occurring after 2.5 years.

The underlying analytical framework employed here seems to a viable means for analyzing CIS electricity usage. One advantage of duality theory is the ability to derive an input-demand equation which is consistent with profit-maximizing and/or cost-minimizing behavior. The dual approach includes all the elements of simpler models previously utilized for the analysis of commercial and industrial electricity usage. It also includes inputs such as labor and capital in the input-demand equation. The statistical significance of the long-run capital coefficient and short-run labor and capital coefficients underscores the importance of including these inputs in an equation modeling CIS electricity consumption. A less robust approach might neglect this aspect of non-residential demand and exclude important explanatory variables. The approach utilized seems to merit additional testing using data from other electric utilities and metropolitan economies.

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