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Modeling Electricity Demand in UAE: Revisit of Time Series Analysis

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ABSTRACT

This paper explains the drivers of electricity demand in the UAE by applying the novel autoregressive distributive lag model (ARDL). This model is well-suited for a small sample size, and it has a robust design in terms of lag selection and length, which mitigates issues of endogeneity and multicollinearity. In addition to GDP and real electricity prices, our model accounts for population, and weather as underlying variables affecting electricity demand in UAE. We employ up-to-date available time-series annual data for the country which covers the period from the year 1985 to 2022. The results suggest that in the short run, except temperature, no other factor seems to have any significant impact on electricity demand. However, in the long run, changes in income, temperature, and population are positively influencing the electricity demand in the UAE. Also, the electricity price appears to be negatively related to the demand for electricity. Overall, our findings show that policymakers' ability to change electricity consumption in the UAE is limited in the short run. Therefore, long-term policies that promote the use of alternative sources of energy and increase consumer awareness through programs that mitigate the impact of climate change factors seem more appropriate.

Keywords: Electricity Consumption, ARDL Estimation, Policy Implication
JEL Classifications: C22, Q41, Q47

1. INTRODUCTION

Since energy is a universal input for nearly all economic activities, estimating and forecasting its future demand hold significant implications for the growth potential of most economies. The seminal work by (Kraft and Kraft, 1978) on the nexus between energy consumption and GDP, showing a bi-directional causality, resulted in various studies using an assortment of econometric approaches to study the link between alternate forms of energy, including electricity, and economic growth (Ahmed et al., 2022; Bashir et al., 2022; Gozgor and Paramati, 2022, among others). As electricity consumption can be taken as an indicator of the level of socioeconomic development of a country, as well as its economic growth, many studies have focused on estimating electricity demand functions and also on examining the causality between electricity consumption and growth.

Recognizing and understanding the main determinants of electricity demand is therefore a crucial element for the economic prosperity and growth of any country. This is because it enables the policymakers in a given country to have in place effective plans to ensure the availability of reliable future electricity to guarantee the prospects of achieving its desired sustainable economic growth goals. Of course, this may involve mega future government projects with financially challenging but very important decisions facing many economies. UAE's solid economic performance in recent years, its strategic location, and unswerving government spending on infrastructure projects, make understanding the existing and projected comportment of electricity demand more important now than ever before. Therefore, it is relevant to conduct a study that investigates the determinants of aggregate electricity demand in the UAE.

The UAE is a federation of seven Gulf Emirates including Abu Dhabi, Dubai, Sharjah, Ajman, Ras Al-Khaimah, Fujairah, and Umm Al-Quwain, is a major oil-exporting country. The country is a major leading business and tourist center in the world, relies greatly on sectors such as oil and natural gas, tourism, real estate, trade, finance, and logistics to support its economy. Such sectors require substantial amounts of electricity to power their activities covering oil and natural gas production and distribution facilities, private and public buildings, hotels, shopping malls, transportation systems, and the like. Accordingly, the demand for electricity in such an economy is mainly influenced by its economic activities and its speedy urbanization progress. The high rates of economic growth witnessed in the country over the last few decades and the various expansion initiatives of UAE's government have led to a significant increase in population and business undertakings over the years. This, and the increasing standard of living resulting in increased use of technology and electronic devices, has further increased the demand for electricity in the country. To meet this growing electricity demand, the UAE has continuously expanded the infrastructure of its power generation and distribution. It depends on a blend of energy sources, containing natural gas, solar power, and clean energy initiatives.

In general, one can distinguish some studies that emphasize the connection between economic growth, urbanization, and electricity demand. Other studies consider the impact of population dynamics such as population growth, demographic trends, and migration patterns as the main drivers of electricity demand. Hot climate is considered in further studies as the main driver influencing electricity demand because air conditioning, cooling systems, and water desalination are high-consuming elements of electricity. Additional studies examine the impact of technological advancements and regulatory policies on electricity consumption patterns. Finally, pricing mechanisms of government policies and energy efficiency standards are other variables that may impact electricity demand. In our paper, we propose a combination of the above-mentioned studies as we include variables reflecting most of such studies.

Our estimation of electricity demand in UAE comprises a multidisciplinary approach that incorporates economic, demographic, technological, and environmental factors to provide insights into possible future electricity consumption patterns in the country. This is in contrast to other approaches that focus on specific factors. Accordingly, we take these multidisciplinary factors to provide an estimate of the demand for electricity in the UAE. This, we think, is crucial and informative for electricity energy planning and local policy decision-makers. Finally, we note that while it is clear that a study that investigates the determinants of aggregate electricity demand in the UAE is needed, very few studies covered the demand for electricity in that country.

The remaining organization of the paper is as follows. Section 2 discusses the background to the work and relevant previous literature. Section 3 details the methodology adopted. Model empirical estimation and interpretation report are discussed in Section 4. Discussion of the study outcomes and policy implications reports are in Section 5.

2. LITERATURE REVIEW

A review of the literature on the demand for electricity in the UAE shows that there are very few published studies that examine this topic when one considers electricity demand for other GCC countries whether on an individual basis or when using panel data for the region. Below, we review the most relevant studies that covered the GCC and individual GCC countries years from 2002 to 2023. We then cover a sample of studies examining electricity demand functions and related topics covering other countries.

Abulibdeh (2021) studied the effect of the pandemic on electricity usage in Qatar's sectors, including residential, industrial, commercial, government, and productive farms. His findings show variability in electricity consumption within and between industries. The greatest difference in electricity use between sectors happened in productive farms, which grew rapidly before the pandemic and were unaffected by it. During the pandemic year, both industrial and commercial electricity use declined dramatically. Other industries saw an increase in electricity use, particularly during the summer months, due mostly to travel restrictions imposed by numerous governments across the world. Mikayilova et al. (2020) examined the regional demand for electricity in Saudi Arabia. Their study concludes that income, price, and population are the key factors influencing electricity demand at the regional level. Although the impacts vary by location, the estimated elasticities are all found to be statistically significant in both the long and short term, with the expected signs across all locations. The income, price and population elasticities in the long run varied across regions from 0.10 to 0.93, from −0.63 to −0.06, and from 0.24 to 0.95, correspondingly. In the short run these values were found (0.05, 0.47), (−0.27, −0.01) and (0.13, 1.49).

Atalla and Hunt (2016) used the structural time series model to explore the factors that influence residential electricity demand in GCC countries. They concluded that, in addition to GDP and real electricity price, the model takes into account population, weather, and a stochastic underlying energy demand pattern, which serves as a surrogate for efficiency and human behavior. They stated that modeling for Qatar and the UAE proved to be questionable because it was very difficult to find preferred models that pass all the diagnostic tests with GDP, the real price of electricity, and the population being individually statistically significant. The reported estimates for price and income elasticities suggest that if policymakers in the region (including UAE), aim to reduce future residential electricity usage, they would have to aim at improving the efficiency of appliances and increase energy-using awareness of consumers, as price increases of electricity won't work. This is because, the estimated UAE short- and long-run income elasticities are also found to be zero while for the real electricity price, short-run elasticity is found to be −0.12 but declines to zero in the long run. Sbia and Shahbaz (2013) used the autoregressive distributed lag model to study the relationship between economic growth, urbanization, financial development, and power consumption in the United Arab Emirates. The empirical findings revealed cointegration among variables and that economic expansion initially increases energy consumption and then decreases it after reaching a certain level of wealth per capita. Financial development increases electricity usage. The link between urbanization and power usage is similarly an inverted U shape. This means that urbanization increases power consumption initially, but after a certain level of urbanization, electricity demand decreases.

Al-Iriani (2005) developed a time series model to investigate the relationship between climate conditions and electric energy consumption in the city of Al-Ain in UAE, focusing on the effect of air conditioning as a major source of electricity consumption. Monthly electricity consumption data spanning the years from 1981 to 2000 was utilized. His findings suggested that the fitted model seemed to represent these relationships quite well and estimates of electricity consumption using the estimated model indicated that a slight reduction in cooling degree need could result in a large reduction in electric energy demand.

In what follows, we review some of the studies that covered other countries beside GCC countries. Stamatiou (2022) investigated the long-run equilibrium connection of electricity consumption in Italy using tourist expansion as a proxy for external growth. The Autoregressive Distributed Lag technique is used and showed a long-term relationship between power usage, foreign visitor arrivals, and economic growth in the country. Foreign visitor arrivals and economic growth were found to have a large impact on power usage, both in the short and long term in Italy.

Onisanwa et al. (2020) applied the autoregressive distribution lag model to assess the factors impacting Nigerian electricity demand. Their findings found that per capita income, population per square kilometer, the number of power users, and electricity shortages are the primary drivers of long-term electricity demand. Romero et al. (2019) investigated the relationship between accommodations and electricity usage in twelve regions of Spain. The authors concluded that there is a positive causal association between electricity consumption and tourist arrivals. Furthermore, the study found that higher-star hotels lead to increased electricity consumption. Al-Bajjalia and Shamaylehb (2017) investigated the impact of six independent variables on energy demand in Jordan. These variables include gross domestic product (GDP), electricity prices, population, urbanization, economic structure, and total water consumption. Their findings indicate that GDP, urbanization, economic structure, and aggregate water usage are substantial and favorably associated with electricity consumption, whereas electricity costs are significant and negatively connected to electricity consumption.

Raza et al. (2016) examined the impact of energy use on economic growth in four South Asian nations. Their findings point to the favorable and large impact of electricity consumption on economic growth. The results of the panel Granger causality test demonstrate that there is a unidirectional causal relationship between electricity use and economic growth. This meant that these countries should pursue development initiatives and low-cost electricity production to boost regional economic growth. Zaman et al. (2012) analyzed the factors that influence the demand for electricity in Pakistan, focusing on economic growth, foreign direct investment, and population growth. Their work used the bounds-testing approach for cointegration and the dynamic short-run causality test. Their findings show that the factors of electricity demand functions are cointegrated and that foreign direct investment, income, and population growth all have a positive relationship with electricity demand. Abosedra et al. (2009) estimated the demand for electricity in Lebanon by using three modeling techniques namely OLS, ARIMA, and exponential smoothing using data from January 1995 to December 2005. Forecasts (in-sample), made by ARIMA (0,1,3) (1,0,0) 12 showed that it is better in terms of lowest RMSE, MSE, and MAPE criteria, followed by exponential smoothing and OLS.

Al-Ghandoor and Samhouri (2009) employed multivariate linear regression to model electricity usage in the Jordanian industrial sector. Their studies suggested that industrial production and capacity utilization are the most critical variables influencing electrical demand. Wolde-Rufae (2006) investigated the long-term, causal link between power consumption per capita and real GDP per capita in 17 African nations. The empirical evidence suggests that only 9 nations have a long-run link between electricity consumption per capita and real GDP per capita, with only 12 countries experiencing Granger causality. For six nations, there was a positive unidirectional correlation from real GDP per capita to electricity consumption per capita; three countries had the opposite causality, and the remaining three had bidirectional causality. Mohamed and Bodger (2005) investigated an electricity forecasting model in New Zealand. The model is based on multiple linear regression analysis, which considers economic and demographic data.

3. ECONOMETRIC METHODOLOGY

The study employs the autoregressive distributive lag model (ARDL), as developed by Pesaran et al. (2001) and Shin et al. (2014), to estimate the electricity demand function. This model is particularly suitable when the variables under examination are either stationary at the level or/and at their first difference. Moreover, the ARDL technique offers notable advantages over conventional models. Firstly, it is well-suited for small sample sizes. Secondly, its robust design in terms of lag selection and length mitigates issues of endogeneity and multicollinearity. Thirdly, it utilizes ordinary least squares for estimations, ensuring that the estimators remain the best linear, unbiased, and efficient (BLUE). A significant departure from traditional methods is that ARDL model helps us to examine both short and long-run relationships among the variables by providing the estimates of relevant coefficients. Furthermore, a standout feature of ARDL models is that they can be used even if the given set of variables is integrated of mixed; thereby enhancing its adaptability.

Following the previous literature, the electricity demand function is identified as:

$$E_t = f(Y_t, P_t, T_t, Z_t) \tag{1}$$

Where, E_t, Y_t, P_t, T_t and Z_t denote the real electricity consumption, real GDP, real electricity price, average temperature and population, respectively. In the log form, the above model can be specified as:

$$lnE_t = \alpha_0 + \alpha_1 lnY_t + \alpha_2 lnP_t + \alpha_3 lnT_t + \alpha_4 lnZ_t + e_t \quad (2)$$

where α's measures the elasticity of demand with respect to these different variables. At first, we carry out unit root tests to examine the time-series properties of all the variables. Subsequently, we use the following ARDL specification of the model given in the equation (2):

$$\Delta(\ln E)_t = \gamma_0 + \sum_{i=1}^{p}\gamma_{i1}\Delta(\ln E)_{t-i} + \sum_{i=0}^{q}\gamma_{i2}\Delta\left(\ln Y\right)_{t-i}$$
$$+\sum_{i=0}^{r}\gamma_{i3}\Delta(\ln P)_{t-i} + \sum_{i=0}^{s}\gamma_{i4}\Delta(\ln Z)_{t-i} + \beta_0(\ln E)_{t-1}$$
$$+\beta_1(\ln Y)_{t-1} + \beta_2(\ln P)_{t-1} + \beta_3(\ln Z)_{t-1} + e_t \quad (3)$$

Here, Δ is the difference operator; *p, q, r* and *s* are the maximum lags used; e_t is the white noise error term and γ_0 is the intercept term. Also, γ_{in} for n ∈ [1,2,3,4] and β_j for j ∈ [0,1,2,3] are short and long-run coefficients, respectively. The ARDL method estimates $(j+1)^k$ number of specifications to identify the optimal lag length for each variable, where *j* is the maximum number of lags to be used and *k* is the number of variables in the equation. An appropriate lag structure is chosen based on a criterion such as Akaike information criterion (AIC) and Schwarz information criterion (SBC) and adjusted R-square.

The procedure involves the use of bounds test wherein the rejection of the null-hypothesis of no cointegration H_O: $\beta_0 = \beta_1 = \beta_2 = \beta_3 = 0$ is tested against the alternative hypothesis of the existence of long-run relationship H_1: $\beta_0 \neq \beta_1 \neq \beta_2 \neq \beta_3 \neq 0$, using the F-statistics. Under this technique, if the estimated F-statistic turns out to be greater than the upper critical bound at a given level of significance, it implies the existence of long-run relationship. However, if the F-statistic is below the lower critical bound, it indicates the absence of a long-run relationship. In case the F-statistic lies within the critical bounds, the test result is inconclusive.

Once the evidence of the long-run relationship between the variables is established, the second step is to estimate the long-run and short-run models. The long-run relationship between the variables is estimated by using the following model:

$$lnE_t = \alpha_5 + \sum_{i=1}^{u}\lambda_{i1}\ln E_{t-i} + \sum_{i=0}^{v}\lambda_{i2}\ln Y_{t-i}$$
$$+\sum_{i=0}^{w}\lambda_{i3}\ln P_{t-i} + \sum_{i=0}^{x}\lambda_{i4}\ln T_{t-i} + \sum_{i=0}^{y}\lambda_{i5}\ln Z_{t-i} + \varepsilon_t \quad (4)$$

Similarly, without the loss of information about the long-run relationship, the re-parameterization of ARDL model gives the information about short-run and error correction adjustment coefficients. This unrestricted error correction representation can be specified as follows:

$$\Delta(\mathrm{lnE})_t = \pi_1 + \sum_{i=1}^{p}\pi_{i1}\Delta(\ln E)_{t-i} + \sum_{i=0}^{q}\pi_{i2}\Delta\left(\ln Y\right)_{t-i}$$
$$+\sum_{i=0}^{t}\pi_{i3}\Delta(\ln P)_{t-i} + \sum_{i=0}^{u}\pi_{i4}\Delta(\ln Z)_{t-i} + \rho ECM_{t-1} + e_t \quad (5)$$

4. EMPIRICAL RESULTS

In this study, we employ time-series annual data from the year 1985 to 2022. The selection of period is guided by the availability of consistent and long time series data on the variables under consideration. The sources of our data are the World Bank, World Development Indicators, Gulf Cooperation Council, Dubai Statistical Centre, and Climate Change Knowledge Portal provided data for electricity production, consumption, GDP, Consumer price

Table 1: Descriptive statistics

Variables (log form)	Mean	Median	SD	Skewness	Minimum	Maximum
Electricity demand (E_t)	9.31	9.35	0.19	−0.20	8.97	9.58
GDP per capita (Y_t)	10.8	10.9	0.25	−0.28	10.3	11.2
CPI - energy, electricity (P_t)	5.30	5.26	0.39	−0.20	4.61	5.81
Temperature (T_t)	3.34	3.34	0.02	−0.57	3.29	3.37
Population (Z_t)	15.2	15.1	0.67	−0.12	14.1	16.0

Source: Own calculations. GDP: Gross domestic product, SD: Standard deviation

Table 2: Unit root tests

Variables	ADF test		PP test	
	At level	At first difference	At level	At first difference
Electricity demand (E_t)	−1.2 (0.61)	−3.82* (0.00)	−0.61 (0.85)	−3.57* (0.01)
GDP per capita (Y_t)	−0.76 (0.81)	−5.15* (0.00)	−1.64 (0.44)	−5.14* (0.00)
CPI - energy, electricity (P_t)	−1.67 (0.43)	−3.47*(0.01)	−1.80 (0.37)	−3.48*(0.01)
Temperature (T_t)	−2.35 (0.16)	−8.24* (0.00)	−2.10 (0.24)	−12.33* (0.00)
Population (Z_t)	−1.47 (0.53)	−2.57** (0.05)	−1.40 (0.56)	−3.33 (0.04)**

Source: Own calculations. The notations *, ** and *** indicate the level of significance at 1%, 5%, and 10% respectively. The values in the parenthesis are *P* values. ADF: Augmented Dicky-Fuller, PP: Phillips–Perron, GDP: Gross domestic product index, temperature, and population. Because of data limitations on the price of electricity, we use the CPI component price of energy and electricity as proxy.[1]

In Table 1, we present the descriptive statistics of the variables. The table indicates the mean, median, minimum, and maximum values and skewness of electricity consumption, price, and income, and the average temperature.

To further examine the time series properties of the variables, in Table 2, we present the unit root tests obtained from Augmented Dicky-Fuller (ADF) Test and Phillips-Perron (PP) test. These results indicate that the null hypothesis of unit-root cannot be rejected at the conventional levels of significance for any variable (at level), thereby indicating that all these time series variables are non-stationary. However, when we consider the first difference of these variables, all these variables turn out to be stationary and follow I(0) process.

In the next stage, we proceed to examine the cointegration relationship among the variables, using the bounds test. The results are summarized in Table 3. It can be seen from the Table that F-statistics (4.15) exceeds the upper critical bound at 5% significance level; therefore, implying that there exists a long-run relationship between the chosen variables.

1. For the missing data points, we used the overall Consumer Price Index as proxy.

Table 3: Bounds test in autoregressive distributive lag model

Significance level	LCB	UCB
1%	3.29	4.68
5%	2.62	3.79
10%	2.26	3.35
F-statistics		8.54*

The notations *, ** and *** indicate the level of significance at 1%, 5%, and 10% respectively. Source: Own calculations. LCB: Lower critical bound, UCB: Upper critical bound

Given the evidence of long-run relationship among the set of given variables, we proceed to estimate the ARDL model as given in equation (4) and (5). The results are summarized in Table 4. The table summarizes both long-run and short-run elasticities as well as the model diagnostic tests. The results suggest that in long-run changes in income, temperature and population have statistically significant impact and are positively influencing the electricity demand in UAE. Also, as expected, the electricity price appears to be negatively related to demand for electricity in the long-run. It is pertinent to note that the long-run elasticity with

Figure 1: (a) Cusum test (autoregressive distributive lag model), (b) Cusum of squares test (autoregressive distributive lag model)

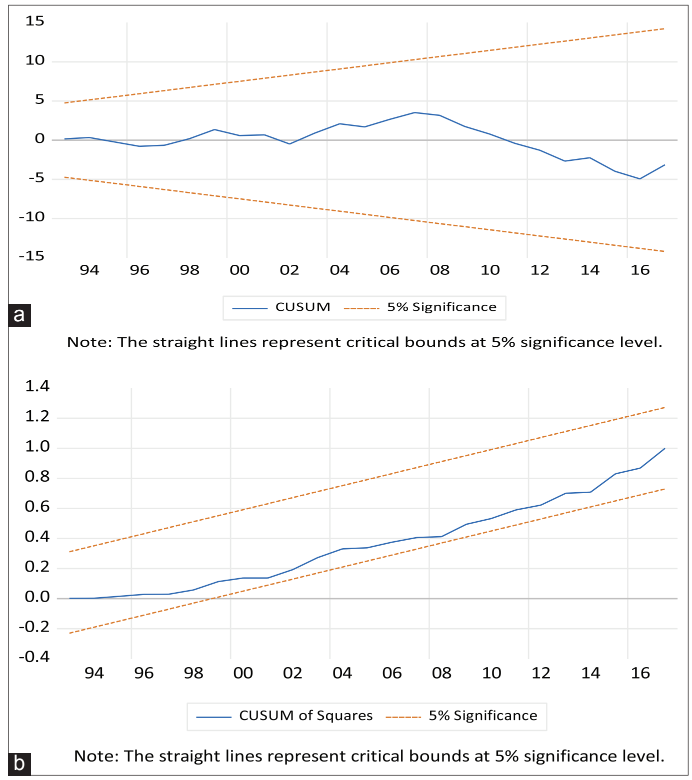

Table 4: Long-run and short-run estimates

Long-run				Short-run			
Variables	Coefficients	t-statistic	p-value	Variables	Coefficients	t-statistic	p-value
Y_t	0.63*	3.55	0.00	ΔY_t	0.07	0.66	0.51
P_t	−0.29**	−2.77	0.05	ΔP_t	0.10	0.46	0.64
T_t	6.19*	5.04	0.00	ΔT_t	−0.13**	−2.35	0.05
Z_t	0.46***	1.82	0.08	ΔZ_t	−0.13	−1.25	0.22
C	−23.61*	−5.01	0.00	ECM(−1)	−0.62*	−7.87	0.00

Diagnostic tests	
Tests	Test statistic
R^2	0.70
Adjusted R^2	0.64
D-Watson	2.10
χ^2ARCH	0.647 (0.413)
χ^2RESET	1.006 (0.326)
χ^2SERIAL	0.731 (0.249)
CUSUM	STABLE
CUSUM square	STABLE

The notations *, **, *** indicate the level of significance at 1%, 5%, and 10% respectively. Source: own calculations respect to temperature turns out to be 6.19; indicating that the electricity demand is highly sensitive to changes in temperature. This is in line with the weather conditions in UAE, as it is one of the hottest in the world with consistently hot and humid climatic conditions. Similarly, concerning income, the electricity demand is relatively inelastic as suggested by the lower magnitude of long-run income elasticity of demand (0.62). In the long run, the size of the population also appears to be an important factor causing a significant upward pressure in the electricity demand.

Further, the results suggest that in short-run, except temperature, no other factor seems to have any statistically significant impact of demand for electricity. However, in response to changes in temperature, the short-run elasticity of demand appears to be 0.13. It is pertinent to note that the rising temperature appears to be an important factor, both in the short run as well as in the long-run, causing an upward pressure in electricity demand. These results suggest that a small reduction in the cooling degrees requirement of buildings and businesses can prove very helpful in a substantial reduction in electricity demand. Further, consistent with theoretical predictions, the coefficient for the error correction term (ECT) which captures the short-run deviation from the long-run equilibrium path is statically significant with a negative sign; implying that the electricity demand changes in response to shocks in these variables. The error correction coefficient suggests that the annual speed of adjustment is 62%. Thus, for any short-run disturbance from the long-run path of this relationship, it takes 1 year and 3 months approximately for the demand to correct the previous deviations.

In the lower panel of Table 4, we also present the model diagnostic tests. The findings indicate that both Breusch-Godfrey Serial Correlation LM Test (χ2SERIAL) and Autoregressive Conditional Heteroskedasticity (χ2ARCH) tests fail to reject their respective null hypothesis; thereby, indicating that the model is free from serial correlation and heteroskedasticity. Further, it can be seen in the Figure 1(a) and 1(b) that both the CUSUM and CUSUM SQUARE plots lie within their 5% critical bounds, therefore, suggesting that our model passes the parameter stability test. Moreover, the Regression Specification Error Term (χ2RESET) test indicates that the null hypothesis of model misspecification can be rejected at the 5% significance level suggesting that the model is correctly specified.

5. CONCLUSION

This paper has attempted to estimate electricity demand function for the UAE applying the novel autoregressive distributive lag model (ARDL), of Pesaran et al. (2001) and Shin et al. (2014). This model is well-suited for a small sample size as our study used time-series annual data from the year 1985 to 2022. This selection of this sample is determined by availability of consistent and long time series data on used variables. Our model accounts for population, and weather as underlying variables affecting electricity demand in the UAE considering the uniqueness of the country's economy and population. The country relies heavily on foreign labor, as roughly 90% of the population is not local, and the high temperature of the country's area as compared to other countries.

The obtained results show that in the short run the electricity demand is perfectly inelastic for changes in income, price, and population. However, in response to changes in temperature, the short-run elasticity of demand was found 0.13. However, our results show, consistent with expectation, that in the long-run changes in income, temperature, and population have a positive impact on electricity demand in UAE. Furthermore, the electricity price appears to be negatively related to demand for electricity in the long run. In addition, we note that the long-run elasticity concerning temperature turns out to be 6.19; indicating that the electricity demand is highly sensitive to changes in temperature. The electricity demand is relatively found to be inelastic as suggested by the lower magnitude of long-run income elasticity of demand (0.62). Furthermore, the size of the population also appears to be an important factor causing a significant upward pressure in the electricity demand in the long run. Accordingly, we think that the empirical results of this study provide policymakers in the UAE with a better understanding of the determinants of electricity demand in the country. Furthermore, such information could be used to formulate policies aiming at achieving efficiency in such consumption in these countries. Conservation policies to avoid waste in electricity consumption adversely affecting the economy should consider the short and long-run elasticities obtained from this study. Overall, our results suggest that the ability of the policymakers to alter the consumption of electricity in UAE is rather limited in the short run as compared to their ability in the long run and therefore while focusing on the long run can emphasize pricing policies, in the short run, improving awareness of consumers by education are more appropriate.

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