Regional Heterogeneous Drivers of Electricity Demand in Saudi Arabia: Modeling Regional Residential Electricity Demand

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Key Points

Saudi Arabia's two waves of energy price reforms in 2016 and 2018 have had different impacts on residential electricity consumption across its regions.

The long-run price responses of residential electricity demand vary across regions. The Saudi Electricity Company's central, eastern, southern and western operating regions have long-run price responses of -0.20, -0.46, -0.25 and -0.23, respectively. The short-run elasticities are -0.10 for the central and western regions, -0.15 in the southern region, while the eastern region's demand does not respond to price changes in the short run.

In the long run, the regions' residential electricity demands respond to income changes according to their income levels. The highest demand response is found in the western region (1.02), followed by the southern (0.54), central (0.44) and eastern (0.27) regions. In the short run, the residential electricity demand in the central and southern regions' does not react to income changes. The elasticities in the eastern and western regions are 0.14 and 0.43, respectively.

Hot weather conditions significantly impact all regions' residential electricity demand. The coefficients/elasticities of the central, eastern, southern and western regions are 0.51, 0.27, 0.75 and 0.66, respectively, in the long run, and 0.26, 0.14, 0.46 and 0.28, respectively, in the short run.

The response of residential electricity consumption to cold weather conditions is only found to be significant in the central and eastern regions. The long-run and short-run elasticities are 0.16 and 0.08 in the central region, and 0.23 and 0.12 in the eastern region.

All regions saw some efficiency improvements in light of the energy price reforms, but there is substantial room for further improvements.

The 2018 reforms made the largest impact in reducing the units of electricity consumed in the central region, while the impact of the reforms on the percentage declines in consumption they precipitated was similar in all regions.

Policymakers should consider the adjustment features of policy shocks in different regions. Across all regions, the full adjustment process takes less than three years, with the western region taking the least amount of time to adjust (1.8 years), and the southern region taking the longest (2.6 years). Both central and eastern regions take 2.1 years to adjust.

1. Summary

Aggregate residential electricity consumption in Saudi Arabia has increased rapidly over the past several decades, largely due to population increases and fast economic growth (SAMA 2019). The growth in electricity consumption has been driven, among other factors, by government-administered prices fixed in nominal terms for years with minor adjustments. Residential electricity demand is determined by a variety of aggregate and disaggregate drivers, which can vary from one region to another. These drivers include, among other things, market concentration, regional wealth, population and income.

Estimating the drivers of electricity demand at the national level might not be representative of the different regions with their different characteristics. Previous studies have focused attention on estimating an aggregated single, national model of electricity demand and comparing estimates across countries. In recent years, Saudi policymakers have reduced energy subsidies in an effort to increase energy efficiency, reduce wasteful consumption alongside and increase government revenues. They also installed several mitigation programs to offset socio-economic shocks (FBP 2017). The Saudi Energy Efficiency Center (SEEC) deployed a series of initiatives aimed at improving the efficiency of residential electricity through multiple channels, such as awareness

campaigns. Given the past and potential future price reforms, Saudi Arabia's policymakers may need to consider the regional drivers of residential electricity demand. A better understanding of regional electricity demand and its drivers may allow for tailored price reform and regional household assistance programs. Determining region-specific price elasticities can help policymakers anticipate demand responses better and estimate the revenues they would get from future price reforms more accurately, since each region can respond differently. This, in turn, could help the government plan better when setting its budget. To emphasize the importance of using accurate responses, let us assume that gross domestic product (GDP) in 2025 will be 10% higher than in 2020. In addition, suppose that the electricity price is increased in 2020 by 100% and then held constant up until 2025. If the long-run price and income elasticities are -0.05 and 0.5, respectively, then there will be no change in electricity consumption in 2025 compared with 2020 ($\text{Price Elasticity} \times \text{Percentage Change in Electricity Price} + \text{Income Elasticity} \times \text{Percentage Change in GDP} = \text{Percentage Change in Electricity Demand}$). However, if the true price elasticity is -0.5, then electricity demand in 2025 will be 45% lower than in 2020. This paper is the first to attempt to model regional residential electricity demand in Saudi Arabia post energy price reform.

2. Background

Saudi Arabia is vast, extending 1,700 kilometers (km) from north to south and 2,000 km east to west (KAPSARC WebGIS Portal 2019). It is the largest country in the Arabian Peninsula, with an estimated area of 2.15 million square km. We divide Saudi Arabia into four regions based on the Saudi Electricity Company's (SEC's) operating areas (Figure 1).

These regions are characterized by their diverse and unique topography and climates (KAPSARC WebGIS Portal 2019). Table 1 highlights these differences, while Figure 2 provides statistics on regional housing types.

Figure 1. The SEC's operating areas.

Source: SEC (2015).

2. Background

Regional characteristics

Table 1. Descriptive statistics of selected regional indicators.

Region	Real per capita GDP in 2018, \$	Weather 1990-2018, degrees Celsius		Population (% of total) in 2018	Average share of residential electricity consumption (% of total), 1990-2018	Average per capita residential electricity consumption growth rates		Population density (person/square km)
		Mean	Std. dev			1990-2018	2015-2018	
Central	21,591	24.23	8.00	32%	30%	3.6%	-6.1%	2,025
East	33,584	24.29	8.87	18%	20%	4.3%	-5.6%	2,180
West	13,267	28.36	6.16	35%	40%	3.6%	-6.1%	3,423
South	23,284	25.40	5.06	15%	10%	5.7%	-3.6%	1,871

Sources: SAMA; NCEI-NOAA; Lopez et al. (2019); KAPSARC WebGIS Portal (2019).

Price, income, weather, and population are conventional drivers of residential electricity consumption (Beenstock et al. [1999], among others). Table 1 summarizes the country's regional heterogeneity. The central region (COA), 29 degrees (°) north to 19° north (KAPSARC WebGIS Portal 2019), is considered the heartland of Saudi Arabia. At its center is Riyadh, the capital city and home to most government agencies, and the third-highest region in GDP per capita (RGDP) terms, at \$21,591 (Lopez et al. 2019). It is also the second most populated region in the Kingdom, home to 32% of the country's total population (SAMA 2019). The region has also been an example of fast urbanization and economic expansion (MOFA 2017). However, the region has suffered from urban sprawl. In fact, the COA is the third densest region, measured in people per square kilometer (km²) (KAPSARC WebGIS Portal 2019). The region also represents

the highest share (47%) of individuals living in villas, and the lowest share (29%) of individuals living in apartments (GaStat 2018d). The climate in the COA is dry, isolated from any natural sources of water; it is hot in the summer and cold in the winter. Since 1990, 95% of the time the temperature in the COA has ranged between 9-43 degrees Celsius (°C) (NCEI-NOAA 2019), while residential electricity consumption per capita in the region grew by 3.6% per year from 1990 to 2018 (SAMA 2019).

The eastern region (EOA), 32° north to 19° north (KAPSARC WebGIS Portal 2019), is the largest region in the Kingdom and the second densest after the western region, with 2,180 people per km². The EOA comes second in both its share of villas (34%) and apartments (45%). The EOA shares its borders with Gulf Cooperation Council (GCC) member states, which enables cross-border trade and

overseas trade with other countries via the Arabian Gulf. The EOA is a significant economic powerhouse for Saudi Arabia, with several resource-intensive industries. Most notably, it contains most of the Kingdom's immense oil reserves and houses the headquarters of the majority state-owned Saudi Aramco, with a market capitalization of some \$1.7 trillion. The region's cities are known for their industrial activity and production capabilities. The region contains 18% of the country's total population (SAMA 2019), and it is the richest region in per capita terms (RGDP=\$33,584 in 2018) (Lopez et al. 2019). Since 1990, the region's residential electricity consumption per capita has grown by 4.2% annually (SAMA 2019). The temperature in the EOA varies in a similar way to the COA, with 95% of its annual temperature ranging between 8°C - 44°C (NCEI-NOAA 2019).

The western region (WOA) lies on the west coast along the Red Sea, 30° north to 19° north (KAPSARC WebGIS Portal 2019). The WOA is home to Mecca and Medina, two of the holiest sites for Muslims. It is the most populated and densest region in Saudi Arabia, with 3,423 people per km² (KAPSARC WebGIS Portal, 2019) and housing 35% of the country's total population (SAMA 2019). This region has the highest share of its population living in apartments (61%). In 2018, it received approximately two million religious pilgrims (GaStat 2018c). The WOA also experiences high temperatures of between 18°C and 39°C, with less variation in temperature than the EOA (NCEI-NOAA 2019). Since 1990, the region's residential electricity consumption has grown on average by 3.6% per year. The region is the Kingdom's least wealthy, with RGDP per capita estimated to be just \$13,267 (Lopez et al. 2019).

Figure 2. Classification of regions by housing types.

Source: GaStat (2018d).

The southern region (SOA) is the least populated of all the regions, with 15% of the country's total population. It is also the least dense region, at 1,871 people per km². It has the second-highest RGDP per capita, at \$23,284 (Lopez et al. 2019). Over the period observed in this study, its residential

electricity consumption grew at 5.7% per year, the highest regional consumption. The SOA also witnessed the smallest regional annual decline in consumption from 2015 to 2018. The SOA's terrain and location (21° north to 16° north) give it a relatively moderate climate. The SOA has

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fertile land and adequate water reserves. The temperature in the region varies less than in any other part of the Kingdom, ranging between 18°C to 33°C (NCEI-NOAA 2019). The government has established several national parks in the SOA for citizens and tourists to enjoy (MOFA 2017). The region has a relatively low share of apartments (30%) and has the highest number of old type houses of any region (33%). The SOA has, in recent years, experienced adverse social and economic shocks resulting from the conflict in Yemen.

2.1 Electricity consumption and price subsidies

Aggregate residential electricity consumption grew rapidly in Saudi Arabia between 1990 and 2015, at an average rate of 4.2% per annum (SAMA 2019), outpacing its RGDP and population growth (SAMA 2019). If these growth rates remain unchanged, electricity consumption will double by 2035.

For most of the country's history, electricity prices in Saudi Arabia have been subsidized and set by the government to support households, with minor adjustments over the years. Saudi Arabia's abundance of oil and gas has allowed the government to supply the Saudi Electricity Company (SEC) with fuels at low administered prices. This subsidy then flows through to consumers, as the electricity is sold to them at below-market prices. For example, from 2000-2015, households that consumed 1,000 kilowatthours (kWh) or less per month paid \$0.013/kWh. However, the SEC charges more per unit of electricity for higher brackets of consumption. For example, households in the 8,001-9,000 kWh bracket paid, on average, \$0.07/kWh (AlGhamdi 2019). Subsidies can provide economic benefits, such as accelerating the development of some economic

sectors, alleviating poverty, and increasing access to energy. However, they could also produce distortions. Energy subsidies encourage wasteful consumption, which counters the Kingdom's sustainable development goals. They also create a burden on the government by forgoing revenue to continue financing unnecessary consumption and weakening private and public investment in alternative sources of energy. Maintaining the subsidy means repositioning public funds for use in other economic activities. This weakens private and public investment in alternative energy sources. Subsidies might also halt the expansion and development of environmentally friendly technologies. Last but not least, the wealthiest households benefit the most from energy subsidies (FBP 2017).

Thus, as a result of large energy subsidies by the government, electricity prices in Saudi Arabia have in fact been declining in real terms since 2000 (AlGhamdi 2019). Among the different drivers of residential electricity consumption among the four regions, electricity prices are the only commonality, as the SEC charges the same prices nationwide.

2.2 Energy price reform

Achieving energy efficiency and a sustainable future for the Kingdom's economy involves undertaking energy price reform (EPR). The fall in oil prices in late 2014 prompted the government to reassess its intervention in the energy market. In 2016 and 2018, Saudi Arabia initiated two waves of energy price reform as part of the Saudi Vision 2030 Fiscal Balance Program. These reforms aimed to deregulate energy prices, reduce energy subsidies and, consequently, induce the rational use of energy and increase government revenues (FBP 2017). Figure 3 details the Kingdom's historical nominal prices of electricity. The years the energy price reforms were introduced are highlighted in red.

Figure 3. Saudi Arabia's historical nominal electricity prices (kWh per Saudi riyal).

Source: AlGhamdi (2019).

Aware of the impact of energy price increases on low-income households, the government launched the Citizen Account Program, a cash transfer program to compensate lower-income households for higher energy prices (FBP 2017).

Before the introduction of price reforms in Saudi Arabia in 2016, the Saudi Energy Efficiency Center (SEEC) began a series of initiatives in 2014 that impacted household demand for electricity. These initiatives aimed to improve the efficiency of residential electricity through multiple channels, such as awareness campaigns. As a result, there was a large drop in residential electricity demand growth in all regions of the country from 2014-2015. These policies prove that behavioural intervention is a very effective way of educating the public on electricity use.

Figure 4 illustrates the Kingdom's regional residential electricity demand growth rates from 2014-2018. It reveals the impact of the first price reform in 2016, which targeted consumers using over 4,000 kWh of electricity per month (AlGhamdi 2019; Al Dubyan and Gasim 2020). This price increase, among other factors, appears to have contributed to the Kingdom's total electricity demand falling by 0.6% in 2016. However, regional responses were different (SAMA 2019). Consumption in the COA and EOA decreased by 2.2% and 4.3%, respectively (SAMA 2019). These comparatively substantial reductions can be explained by the fact that these regions are wealthier than the others, and the EPR in 2016 was mainly targeted at the consumption of high-income groups (AlGhamdi 2019). These regions also contain a larger portion of wealthier households living in

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large homes, such as villas that might consume more than 4,000 kWh per month (GaStat 2018b). This might explain why we see some heterogeneous responses during the first price reform. In contrast, the WOA, the poorest and warmest region, and the SOA, which is wealthier and comparatively cooler, increased their consumption by 1.7% and 3.5%, respectively (SAMA 2019).

The second price reform in 2018 targeted households consuming under 4,000 kWh per month (AlGhamdi 2019), and the responses it elicited were much more substantial than the 2016 reform. As a result, total residential electricity consumption declined by 9.1% nationwide (SAMA 2019). While consumption across the regions responded similarly to price deregulation, they were driven by different components. The impact of the 2018 price reform led to a -10.7% change in consumption in the COA, -8.8% in the EOA, -8.1% in the WOA, and -8.1% in the SOA (SAMA 2019).

It is particularly hard for policymakers to dissect the effects of increased prices on the decline in

consumption since there are other variables at play. It is even more challenging to use an aggregated response in demand to evaluate more granular issues such as efficiency gains and changes in consumer behavior, which will naturally vary regionally. These facts underscore the importance of disaggregation, which is key to identifying the root causes of these differing responses. Aggregation omits considerable variation across regions, and valuable information may, therefore, be forgone (Lee, Pesaran, and Pierse 1990). Nevertheless, there have been signs of efficiency gains as a result of the reforms at the aggregate level. Figure 5 shows that the number of households that consumed over 8,000 kWh/month declined from 21% in 2015 to 11% in 2018. During the same period, those consuming between 1,000-2,000 and 2,001-4,000 kWh/month increased by 8% and 4%, respectively. Additionally, the General Authority of Statistics' Household Energy Survey 2018 measured a 10% increase in new households adopting electrical power saving devices from 2017-2019, from 26% to 36% (GaStat 2018a).

Figure 4. Annual growth rate (%) of total and regional residential electricity consumption.

Source: SEC via SAMA (2019).

Figure 5. Percentage of consumption invoices issued for the different consumption brackets.

Source: ECRA (2016, 2017, 2018, 2019).

3. Literature Review

This section provides an overview of the existing literature on electricity consumption in Saudi Arabia. The literature includes a variety of modeling techniques that attempt to capture electricity consumption behaviors. For example, Matar (2017) has implemented an optimization-based model to estimate electricity price elasticities. However, for the purpose of this study, we will mainly focus on studies that have analyzed regional residential electricity demand using econometric methods. To the best of our knowledge, there are only two studies, Diabi (1989) and Mikayilov et al. (2019), that considered regional electricity demand. Both studies considered total, but not residential, consumption. Hence, we also included studies examining total residential electricity consumption, i.e., Kingdom-wide, in our review.

Table 2 provides a summary of our literature review, including the methods used, the estimation period, and the estimated elasticities of each study.

As discussed in previous sections, regional behavior is not necessarily homogeneous, which makes it essential to investigate regional elasticity demand. Diabi (1998) considered a panel of five regions (i.e., central, western, eastern, southern and northern) and applied different panel methods to estimate their total electricity consumption from 1980-1992. The study found that income elasticities ranged between 0.11 to 0.49 and 0.05 to 0.33 for the long and short run, respectively. The study also found the price elasticities in the long run to range between -0.14 and 0.00, and, for the short run, -0.12 and 0.00. However, the study cannot be considered a regional analysis of electricity consumption, as the region-specific elasticities/coefficients were not reported. Moreover, the obtained coefficients should be considered with caution, as the analysis did not account for some important properties of panel data,

such as integration, cointegration, cross-sectional dependency, and cross-sectional heterogeneity. For example, it is commonly accepted that not addressing the integration/cointegration properties of data can lead to spurious results (Engle and Granger 1987). Seminal studies, such as Pesaran (2015), Baltagi and Pesaran (2007), among others, argue that if the presence of cross-sectional dependencies is ignored, then conventional estimators, like the ones used in this study, can result in misleading inferences and inconsistent estimators. However, we acknowledge that the missing integration, cointegration, cross-sectional dependency, and cross-sectional heterogeneity data properties should not be considered as a shortcoming of Diabi (1998) because many of these properties were not widely addressed in the scientific community at the time the study was conducted. Furthermore, many changes have taken place since the study was conducted, such as the government's efforts to increase energy efficiency and the electricity price reforms of 2016 and 2018.

Mikayilov et al. (2019) is only the study that conducted a time series analysis of electricity consumption in the four regions of Saudi Arabia that this study addresses. They applied cointegration and error correction methods to the annual times series data of the regions from 1990-2016. The demand equation that they estimated includes the explanatory variables of income, price and population. They proxied income with total GDP and total disposable income, depending on the region. They found long-run income elasticities, price and population elasticities for the COA, EOA, SOA and WOA in the ranges of [0.10, 0.93], [-0.61, -0.06] and [0.24, 0.95], respectively. Their estimated short-run elasticities for income, price and population were in the ranges of [0.05, 0.47], [-0.27, -0.01] and [0.13, 1.49], respectively. Before the current study, this was the only available regional electricity study

for Saudi Arabia, and it has some limitations. For example, total GDP and disposable income, used as income measures, are the same across all regions. Additionally, this study looks at total regional electricity consumption without analyzing regional residential consumption. As such, the results may not represent the true behavior of residential electricity demand.

As detailed in the table below, a number of studies estimated the elasticities of total electricity consumption. They used a variety of estimation methods to provide price elasticities ranging from -0.12 to 0.00 and -1.24 to 0.00 for the short and long run, respectively. Most of these studies also estimated the income elasticities to range between 0.05 to 0.33 and 0.09 to 1.65 for the short and long run, respectively (Diabi 1998). While it is essential to understand the impact of income and prices on total electricity consumption, these elasticities might not be representative of residential electricity consumption in Saudi Arabia.

Eltony and Mohammad (1993) and Al-Sahlawi (1999) have estimated residential electricity consumption using the ordinary least squares (OLS) method. However, they did not provide evidence that they

checked for stationarity, which may indicate biased coefficients. Atalla and Hunt (2016) used the structural time series model (STSM) to estimate the price elasticities to be -0.16 for the short and long run, and 0.48 for the long-run income elasticity. Al Dubyan and Gasim (2020) recently investigated residential electricity consumption in the Kingdom using STSM, finding price elasticity to be -0.09 in the long and short run and income elasticity to be 0.22 in the long run. Hasanov et al. (2019) used cointegration techniques to estimate the Kingdom's residential electricity demand. They found the long- and short-run price elasticities to be -0.35 and -0.13, respectively. Their estimated long-run income elasticity is unity. The last three studies, Atalla and Hunt (2016), Hasanov et al. (2019) and Al Dubyan and Gasim (2020), found that demand is irresponsive to income in the short run.

The reviewed literature shows that no individual study has investigated residential electricity demand at the regional level in Saudi Arabia. The current study aims to fill this gap by modeling residential electricity demand at the regional level, obtaining elasticity estimates, and revealing the main drivers of demand and their contributions to changes in demand over time.

3. Literature Review

Table 2. Summary of the literature review on total and residential electricity demand in Saudi Arabia.

Study	Electricity variable	Period and method		Price elasticity		Income elasticity		Remarks
				SR	LR	SR	LR	
Eltony and Mohammad (1993)	REC CEC IEC	1975-1989 (P) OLS		-0.14	-0.14	0.196	0.20	Coefficients included are for REC. No evidence of checking for stationarity before using OLS.
Diabi (1998)	TEC	1980-1992 (P)		-0.12 to 0.00	-0.14 to 0.00	0.05 to 0.33	0.09 to 0.49	Methods used: OLS, RE, FE, MLE, CCTA, and CHTA.
Al-Sahlawi (1999)	REC IEC AEC	1975-1996 (T) OLS		-0.10	-0.50	0.13	0.70	Coefficients included are for REC. No evidence of checking for stationarity before using OLS.
Atalla and Hunt (2016)	REC	1985-2012 (T) STSM		-0.16	-0.16	-	0.48	Study conducted on the GCC, but the elasticities reported are for Saudi Arabia. Found the effect of CDD and HDD to be 0.16 and 0.50, respectively.
Hasanov et al. (2019)	REC	1985-2017 (T)		-0.13	-0.35	-	1.01	
Mikayilov et al. (2020)	Regional TEC	1990-2016 (T) Multiple methods	COA	-0.08 to -0.01	-0.58 to -0.66	0.15 to 0.41	0.40 to 0.93	Methods used: DOLS, CCR, FMOLS. Elasticities differ by region.
			EOA	-0.23 to -0.09	-0.63 to -0.36	0.05 to 0.18	0.10 to 0.20	
			SOA	-0.27 to -0.15	-0.13 to -0.06	0.08 to 0.22	0.12 to 0.36	
			WOA	-0.10 to -0.03	-0.61 to -0.43	0.16 to 0.47	0.43 to 0.47	
Al Dubyan and Gasim (2020)	REC	1985-2018 (T) STSM		-0.09	-0.09	-	0.22	Found the effect of CDD to be 0.39 for both the long and short run.

Glossary

REC	Residential electricity consumption	FE	Fixed effects model	VAR	Vector autoregression
CEC	Commercial electricity consumption	CCTA	Cross-sectionally heteroskedastic and timewise autoregressive model	CCR	Canonical cointegrating regression
IEC	Industrial electricity consumption	CHTA	Cross-sectionally correlated and timewise autoregressive model	ECM	Error correction model
OLS	Ordinary least squares	FMOLS	Fully modified ordinary least squares	STSM	Structural time series model
MLE	Maximum likelihood estimation	DOLS	Dynamic ordinary least squares		
RE	Random effects model	VECM	Vector error correction model		

SR – Short run

P – Panel data

LR – Long run

T – Time-series data

4. Theoretical Framework

The current paper follows the theoretical framework of Beenstock and Dalziel (1986), Hasanov et al. (2016), and Atalla and Hunt (2016), among others. In other words, it is assumed that electricity consumption in the residential sector is driven by income levels, electricity prices, weather conditions and population. To avoid the potential heterogeneity issues across the regions and make the results and electricity consumption figures comparable with the findings of other studies, we use the specification in per capita terms.

Where:

De_t is per capita residential electricity consumption, Y_t is per capita income in real terms, P_t is the weighted average residential electricity price in real terms, CDD_t is annual cooling degree days, HDD_t is annual heating degree days, and $UEDT_t$ is the underlying energy demand trend (discussed in the methodology section) for residential electricity consumption.

$$De_t = f(Y_t, P_t, CDD_t, HDD_t, UEDT_t) \quad (1)$$

5. Econometric Methodology

This study uses the structural time series modeling (STSM) approach developed by Harvey (1989) to model the electricity demand relationship. The relationship is modeled using different structures of time series data. This approach enables the detection of different types of interventions within the sample, which helps avoid problems such as misspecification and the distortion of parameter estimations (Castle et al. 2015). This approach also enables us to model the varying nature of the parameters (Harvey 1989, 367). The STSM approach applies the maximum likelihood estimation technique when estimating the model's parameters by utilizing the Kalman filter algorithm (Kalman 1960). The following is a summary of the STSM approach. Let us consider the following equation:

$$y_t = z_t' \alpha_t + x_t' \beta_t + \epsilon_t, t = 1, \dots, T \quad (2)$$

Where:

y_t is the dependent variable; z_t' is a vector of the components of y_t , the slope, level, seasonal, and cycle components, which might be stochastic. The components of y_t form the stochastic trend, with a deterministic trend particular to the stochastic trend, which is referred to in energy economics literature as the underlying energy demand trend (UEDT) (Hunt et al. 2000). The UEDT can be interpreted as displaying, as in the deterministic trend case, the effects of technological improvements, among other directly unmodeled factors. x_t' is the vector of explanatory variables; ϵ_t is the error term; α_t and β_t are the parameters to be estimated, which are potentially time varying. T is the number of observations. The model (2) can be put into a state-space form in order to apply the Kalman filter algorithm as follows:

$$y_t = [z_t' x_t'] \alpha_t^\dagger + \epsilon_t, t = 1, \dots, T \quad (3a)$$

$$\alpha_t^\dagger = \begin{bmatrix} \alpha_t \\ \beta_t \end{bmatrix} = \begin{bmatrix} M & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \vartheta_t \end{bmatrix} \quad (3b)$$

Equation (3a) is an observation or measurement equation, and (3b) is a state or transition equation. M is a matrix relating the parameters and lagged values of the components of the independent variable, I is a unit matrix. $\eta_t=0$ is a special case of the time-varying component. When the variation is zero, one can conclude that the components of a dependent variable are deterministic. Likewise, $\vartheta_t=0$ means the parameters of the independent variables are constant over time. The model can be enhanced with lagged values of the dependent and independent variables (Harvey 1989, 367-372). In other words, the model can be written in the autoregressive distributed lagged (ARDL) form. This allows the model estimated by the STSM to be expressed in the conventional error correction model (Harvey 1989, 371-372). Consequently, after estimating the parameters of the model using the STSM approach, one can specify the long-run and short-run coefficients, and the speed of adjustment (SoA) coefficient (Harvey 1989, 371-372). The STSM approach allows us to test whether the variables under investigation share common trends and a cointegrating relationship (Harvey 1989, 449-456). The details of the tests employed in this study can be found in Nyblom and Harvey (2000, 2001). The estimations are done utilizing the 8.40 version of STAMP by Koopman, Lit, and Harvey (1995-2018). Readers can find the details of the STSM approach in Harvey (1989), Koopman et al. (1999), and Commandeur and Koopman (2007), among others.

The study uses the augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1981) to test the variables for stationarity features. The paper uses cointegration tests by Nyblom and Harvey (2000, 2001) and Johansen (1988, 1995) to test the cointegration relationship between the variables.

Decomposition Analyses

In economics, decomposition analysis (Ang et al. [1998]; Ang and Zhang [2000], and Ang [2005, 2015], among others) is used to measure the individual physical effects of drivers on an indicator of interest. The technique relies on the idea of an absolute (physical) value of a 1% relative change. The absolute and relative changes in variables y and x from point $t-1$ to t can be expressed as follows:

$$\begin{aligned} \text{absolute change} &= y_t - y_{t-1}, \\ \text{relative change} &= \frac{y_t - y_{t-1}}{y_{t-1}} \end{aligned} \quad (4)$$

It is known from calculus that:

$$\begin{aligned} \Delta \ln y_t &= \ln y_t - \ln y_{t-1} = \ln \frac{y_t}{y_{t-1}} = \\ \ln \left(\frac{y_t - y_{t-1}}{y_{t-1}} + 1 \right) &\approx \frac{y_t - y_{t-1}}{y_{t-1}} \end{aligned} \quad (5)$$

In other words, for relative change we have:

$$\frac{y_t - y_{t-1}}{y_{t-1}} \approx \Delta \ln y_t \quad (5)$$

That is, to measure the relative change in a variable, the absolute change of the logarithm of that variable is used (the approximation works better for small relative changes). This formula is widely used in economics literature for measuring relative change. In other words, $\Delta \ln y_t$ is used for relative change and $100 * \Delta \ln y_t$ is used for percentage changes.

Accordingly, the formula for an absolute (physical) value of a 1% relative change is as follows:

$$\text{the absolute value of 1\% relative change} = (y_t - y_{t-1}): \quad (6)$$

$$\left(\left(\frac{y_t - y_{t-1}}{y_{t-1}} \right) * 100 \right) \dots \dots \dots$$

The following can be written to consider the relative change of relationship (5) in formula (6):

$$\text{the absolute value of a 1\% relative change} = \frac{\Delta y_t * 1}{\Delta \ln y_t * 100} \quad (7)$$

Let us consider that y_t is the dependent variable, x_t is an independent variable, and α is the elasticity of y_t with respect to x_t . Then considering that $\frac{\Delta y_t * 1}{\Delta \ln y_t * 100}$ is the absolute value of a 1% relative change in y_t , α is the response of y_t to a 1% change in x_t . Considering that α is the response of y to a 1% change in x (expressed as a percentage), $100 * \Delta \ln x_t$ is the total change in x (in percent), then $\alpha * 100 * \Delta \ln x_t$ would be the total change in y (in percent) due to the change in x , moving from time $t-1$ to time t . Now, considering that $\alpha * 100 * \Delta \ln x_t$ is the total percentage change in y due to the change in x , ($100 * \Delta \ln x_t$), and $\frac{\Delta y_t * 1}{\Delta \ln y_t * 100}$ is the absolute value of a 1% relative change in y_t , then the term $\frac{\Delta y_t * 1}{\Delta \ln y_t * 100} * \alpha * 100 * \Delta \ln x_t$ is the absolute change (in physical units) in y due to the change in x , moving from time point $t-1$ to t . In short, the absolute change in y (in physical units) due to factor x , moving from time $t-1$ to t , can be formulated using the formula below:

$$\frac{\Delta y_t}{\Delta \ln y_t} * \frac{1}{100} * \alpha * 100 * \Delta \ln x_t \quad (8)$$

The formula is also valid for the changes from time $t-h$ to time t . Interested readers can refer to Ang et al. (1998); Ang and Zhang (2000), Ang (2005, 2015), among others, for different decomposition methods, and further details of the method employed in this study.

6. Data

To estimate regional residential electricity consumption, we use annual data from 1990-2018. The period studied is subject to the availability of historical electricity consumption data. The following provides a brief summary of the variables used in this study:

Residential electricity consumption (*RES*)

is the dependent variable and is defined as the annual household electricity demand in megawatthours (MWh). To control for regional population variation, the variable is expressed in per capita terms using the population data discussed below. The data series is sourced from the SEC for 1990-2004, and the remaining years up to 2018 are from the Saudi Arabian Monetary Authority Annual Statistics for 2018 (SAMA 2019). The population data from 2007-2018 for the four regions were aggregated from the 13 administrative regions/provinces found in SAMA (2019). Data for 1990-2006 were collected from the population surveys of the General Authority for Statistics of Saudi Arabia. Figure 6 below displays RES per capita in the four regions over the studied period.

The residential electricity price (*P*) represents the price of household electricity in Saudi riyals (SAR) per kWh. The prices were calculated by KAPSARC researchers as the weighted average of the residential electricity prices taken from Saudi Arabia's Electricity and Cogeneration Regulatory Authority's data (Al Dubyan and Gasim 2020). The consumer price index (CPI), rebased to 2010, is used to convert nominal price values into real values. CPI 2013=100 data for 2001-2018 were collected from SAMA (2019), while CPI 2007=100 data for 1990-2000 were obtained from SAMA (2017), and both were rebased to 2010.

Regional **Income (*I*)** levels were not available for Saudi Arabia. Thus, we use the regional GDP estimated by Lopez et al. (2019) as a proxy for regional household income, as it is the best publicly available regional income measure. Second, we believe it is better to use regional GDP rather than total disposable income, or total GDP as Mikayilov et al. (2019) did. Third, several previous studies have successfully used GDP as a measure of income in their energy/electricity demand analyses. The regional GDP data in this study are expressed in million SAR per capita.

Figure 6. Residential electricity demand (MWh) per capita.

Source: SAMA (2019).

6. Data

Cooling degree days (CDD) represents the sum of the annual regional days that exceeded 21.1°C, following Atalla et al. (2015). This variable aims to capture the amount of cooling that was required to achieve a comfortable indoor temperature in households. To calculate the variable, we select three cities to represent each region, calculate the weighted average of the heat index temperatures based on their population, and quantify the days in a year for each region in which their temperatures exceeded 21.1°C. The cities' temperature data was obtained from the National Centers for Environmental Information, National Oceanic and Atmospheric Administration (NCEI-NOAA).

Heating degree days (HDD) captures the heating required for each region. We followed the CDD calculation method to calculate the annual days in each region in which temperatures were below 18.3°C (Atalla et al. 2015). The temperature data was obtained from NCEI-NOAA.

To calculate CDD and HDD, NOAA's National Weather Service (NWS) Heat Index (HI) is used to measure the human-perceived equivalent temperature. The NWS HI is calculated through multiple regression analysis of Steadman's equations (Steadman 1979) for wind and solar radiation, through using only two independent variables, ambient temperature (T) and relative humidity (Rh) (Rothfusz 1990). To the best of our knowledge, ours is the first study to use humidity-adjusted CDD and HDD data.

Three equations are used to calculate the NWS HI, where T is in degrees Fahrenheit (°F), and Rh is expressed as a percentage:

The following equation is used to calculate NWS HI for humidity above 40% and ambient temperatures above 80°F:

$$\begin{aligned} HI = & -42.379 + 2.04901523T + 10.14333127Rh - \\ & 0.22475541TRh \times 6.83783 + 10^{-3}T^2 - 5.481717 \\ & \times 10^{-3}Rh^2 + 1.22874 \times 10^{-3}T^2Rh + 8.5282 \times \\ & 10^{-3}TRh^2 - 1.99 \times 10^{-6}T^2Rh^2 \end{aligned}$$

When the ambient temperatures are between 80°F and 112°F, and Rh is less than 13%, the following adjustment is subtracted from HI.

$$Adj = \left[\frac{13 - Rh}{4} \right] \times \sqrt{\left[\frac{17 - \text{abs}(T - 95)}{17} \right]}$$

When the ambient temperatures are between 80°F and 87°F, and Rh is higher than 85%, the following adjustment is added to HI.

$$Adj = \left[\frac{Rh - 85}{10} \right] \times \left[\frac{87 - T}{5} \right]$$

Since the NWS HI requires relative humidity values that our data set does not include, we have applied August-Roche-Magnus approximation equations to calculate relative humidity.

$$Rh = 100 \times \left(\frac{e^{\left(\frac{17.625TD}{243.04 + TD} \right)}}{e^{\left(\frac{17.625T}{243.04 + T} \right)}} \right)$$

7. Empirical Estimation Results

7.1. Unit root test results

Before conducting the cointegration analysis, we examine the stationarity of each variable involved in the model using a unit root test. This study uses the augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1981). The ADF's null hypothesis indicates whether or not a variable has a unit root, i.e., whether or not it is non-stationary. While conducting the ADF test, the optimal lag values are determined by Schwarz information criterion (SIC), as we use a

maximum lag value of two. Table 3 summarizes the findings of the unit root tests.

We can conclude from the results shown in Table 3 that all the explanatory variables are integrated of the same order, $I(1)$, for most of the regions, except for HDD. If there is a long-run relationship among other variables, adding the stationary (HDD) variable to the cointegration space does not alter the results. In the next step, we employ the cointegration tests.

Table 3. Summary of the unit root test findings.

Unit root ADF test results			
Region	Variables (in logs)	Level	First difference
COA	Electricity demand per capita	-2.62	-2.90*
	GDP per capita	-1.48	-3.44**
	CDD	-1.60	-7.79***
	HDD	-4.33***	-7.90***
EOA	Electricity demand per capita	-0.53	-5.18***
	GDP per capita	-2.27	-3.73***
	CDD	-2.14	-10.20***
	HDD	-3.83***	-8.01***
WOA	Electricity demand per capita	-1.07	-3.49**
	GDP per capita	-1.17	-3.85***
	CDD	-2.46	-7.94***
	HDD	-3.78***	-8.09***
SOA	Electricity demand per capita	-0.54	-4.02***
	GDP per capita	-1.23	-5.91***
	CDD	-1.73	-6.85***
	HDD	-1.67	-7.59***
All	Electricity price	0.019	-4.31***

Note: The intercept only case is used in this analysis.

***, **, * Indicate rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

7. Empirical Estimation Results

7.2. Cointegration test results

After examining the variables for stationarity properties and concluding the same order of integration, one can test the variables for their long-run common trends. This exercise utilized the cointegration test proposed by Nyblom and Harvey (2000, 2001) and maximum eigenvalue and trace tests proposed by Johansen (1988, 1995). The results of the cointegration tests are provided in Tables 4 and 5.

As can be seen from Table 4, in all four regions, the number of eigenvalues statistically different from zero is one. The number of cointegration vectors in the system is defined by the rank, and the latter is equal to the number of eigenvalues different from zero. Hence, based on these results, one can conclude that all cases have only one cointegrating relationship.

As a robustness check, the trace and maximum eigenvalue tests (Johansen 1988, 1995) are also employed, and the results are given in Table 5.

Table 4. Summary of the cointegration test results (Nyblom and Harvey 2000, 2001).

Cointegration test results					
Region			Eigenvalues		
COA	0.006020	1.093e-19	9.132e-21	-9.979e-21	-4.337e-19
EOA	0.007569	4.514e-36	1.505e-36	0.0000	-1.084e-19
SOA	0.006997	4.337e-19	1.599e-20	-3.925e-21	-a
WOA	0.007890	5.129e-19	1.117e-20	-2.198e-20	-a

Notes: a = HDD variable does not enter the specification, and the corresponding matrix is 4x4.

Table 5. Summary of the cointegration test results (Johansen 1988, 1995).

Cointegration test results								
	COA		EOA		SOA		WOA	
	Trace stat	Max stat	Trace stat	Max stat	Trace stat	Max stat	Trace stat	Max stat
$r=0$	53.79 (0.01)	28.71 (0.04)	108.67 (0.00)	51.52 (0.00)	49.24 (0.04)	32.96 (0.01)	57.96 (0.00)	30.35 (0.02)
$r \leq 1$	25.07 (0.16)	22.45 (0.03)	57.14 (0.01)	26.08 (0.08)	16.28 (0.69)	8.76 (0.85)	27.61 (0.09)	17.81 (0.14)
$r \leq 2$	2.62 (0.98)	2.53 (0.97)	31.06 (0.04)	19.59 (0.08)	7.52 (0.52)	4.69 (0.78)	9.80 (0.30)	8.83 (0.30)
$r \leq 3$	0.09 (0.76)	0.09 (0.76)	11.47 (0.18)	9.99 (0.21)	2.83 (0.09)	2.83 (0.09)	0.97 (0.33)	0.97 (0.33)

Notes: Trace stat = trace test statistics value; Max stat = maximum eigenvalue test statistics value; r is the number of cointegrated equations under the null hypothesis; p-values are in parenthesis and are taken from MacKinnon, Haug and Michelis (1999).

The results show that both trace and maximum eigenvalue tests conclude one cointegrating relationship for SOA and WOA. The maximum eigenvalue test concludes one cointegration for the EOA, while the trace test concludes one cointegration for the COA. As Lütkepohl, Saikkonen and Trenkler (2001) concluded, in some circumstances for small samples, trace tests often produce more inaccurate sizes, rejecting the null frequently, than the maximum eigenvalue tests. However, Lütkepohl, Saikkonen and Trenkler (2001) prefer to use trace tests based on simulation results, although there is no proof that one test is better than the other. Therefore, given that our tests produced a cointegrating relationship, we can conclude that there is one cointegrating vector in all regions, based on the trace and maximum eigenvalue tests.

Hence, combining the results of Nyblom and Harvey (2000, 2001) and Johansen (1988, 1995) with the results we obtained, we can conclude that there is only one cointegrating relationship in all four regions.

7.3. Results of empirical estimations

Having concluded the existence of one cointegrating relationship for all the regions, we can proceed to a single equation estimation. Using the STSM approach, the equations for four regions are estimated, and the results are summarized in Table 6. For the empirical estimations, we estimated the following specification with one lag:

$$de_t = \alpha_0 + \alpha_1 de_{t-1} + \beta_0 y_t + \beta_1 y_{t-1} + \gamma_0 p_t + \gamma_1 p_{t-1} + \delta_0 cdd_t + \delta_1 cdd_{t-1} + \vartheta_0 hdd_t + \vartheta_1 hdd_{t-1} + uedt \quad (4)$$

The variables are logarithmic forms of the variables, as defined in the theoretical framework section. The detailed estimation results can be found in Table A1 in Appendix 1.

The empirical estimations show that, in the long run, income and price both have statistically significant impacts on residential electricity consumption in all regions. In the short run, demand for electricity in the residential sector does not respond to income in the COA and SOA, while it is irresponsive to price changes only in the EOA. The potential variation in the responses of electricity consumption to its drivers is also examined for the period estimated. The estimation results did not reveal any variation in parameters for the studied period. In other words, the responses of residential electricity demand to the changes in its drivers remain constant for the investigated period.

CDD has a significant impact on residential electricity demand in all regions, while HDD was found to have an impact only in the COA and EOA regions.

The speed of adjustment coefficients for all regions are found to be in line with the expected interval and are statistically significant.

7. Empirical Estimation Results

Table 6. Long and short-run elasticities.

Cointegration test results

Region	Income		Price		CDD		HDD		SoA
	Short run	Long run	Short run	Long run	Short run	Long run	Short run	Long run	
COA	-	0.44	-0.10	-0.20	0.26	0.51	0.08	0.16	-0.48
EOA	0.14	0.27	-	-0.46	0.14	0.27	0.12	0.23	-0.48
SOA	-	0.54	-0.15	-0.25	0.46	0.75	-	-	-0.38
WOA	0.43	1.02	-0.10	-0.23	0.28	0.66	-	-	-0.57

Notes: “-” = the coefficient is found to be insignificant, and the appropriate term is excluded from the specification. The coefficients reported in the table are all statistically significant at at least the 10% significance level. SoA= speed of adjustment.

8. Discussion of the Findings

The estimation results concluded that the responses of electricity demand in Saudi Arabia's residential sector to income, price, and temperature vary by region. As mentioned by Lee et al. (1990), there might be a loss of information from working with aggregate data instead of sectoral or regional-level data. In this regard, our findings, which show variations across regions, are supportive of their conclusion.

Based on the empirical estimation results given in Table 6, one can see that regional long-run income elasticity ranges from 0.27 to 1.02. The highest long-run income elasticity is found for the WOA, and the lowest is found for the Eastern region. This finding is expected, as the EOA is Saudi Arabia's richest region, and the WOA is the country's poorest region (Table 1). As discussed in Chang (1977, 1980) and Chang and Hsing (1991), and revised by Mikayilov et al. (2020), a certain commodity (residential electricity consumption in our case) can be considered as a luxury good up to a certain income threshold. Above that threshold, the demand response to changes in income starts to decrease. The threshold will differ across regions and countries and according to the commodity. The physical need for a commodity is bounded. Subsequent income rises will not impact demand to the extent that previous income rises did. In other words, the response of demand to income is non-linear: changes in demand will moderate after a certain rise in income. In this regard, smaller demand responses to income are expected for wealthier regions, with the opposite being true for poorer regions. However, we found long-run income elasticity to be higher in the SOA than the COA, which contradicts the points above. Considering the representative quality of GDP levels, not only GDP per capita, sheds light on this finding. Although in per capita terms the SOA is the second richest region in the Kingdom, the COA is the richest region in terms of total GDP. The SOA

region has also had the smallest population growth among the regions since 2009 (SAMA 2018) and has the highest share of old house types of any region. In contrast, the COA is more modernized and has greater availability of efficient technologies and appliances. These points may explain the larger income elasticity of the SOA than the COA. The short-run income effects are found to be statistically significant only in the EOA and WOA, the richest and poorest regions. Despite being the richest region, the short-run income elasticity in the EOA was also found to be significant. This finding indicates that there might be a wasteful use of electricity in the EOA, which a reduction in income would reduce. The short-run income impact for the WOA can be explained by its further need for electricity. Consequently, a change in income in the region would result in a consumption response, even in the short run.

Since no previous study has looked into regional residential electricity consumption in Saudi Arabia, the results of this paper are not directly comparable with any previously published findings. Nevertheless, we can provide indirect comparisons. Our long-run income elasticities are more or less in line with Atalla and Hunt (2016), Hasanov et al. (2019), and Al Dubyan and Gasim (2020), all of whom modeled total residential electricity demand in the Kingdom. These studies all concluded that income does not affect demand in the short run. In contrast, this study found a significant short-run impact of income in two of the country's four regions, as determined by the SEC's operating areas.

The long-run price elasticities for the WOA, COA, and SOA were largely similar, at around -0.2. The higher long-run price elasticity in the EOA may be indicative of its ability to substitute less efficient appliances with efficient ones and/or change its electricity consumption behavior. It is possible that households

8. Discussion of the Findings

in other regions only use electricity to meet their essential needs. Therefore their ability to reduce their electricity use could be below that of the EOA. These findings can also be interpreted according to the income-demand phenomenon. For example, rich consumers who may have extra consumption bandwidth for a certain commodity can reduce their consumption quite easily when its price rises. Furthermore, consumers with greater purchasing power can decrease their consumption of electricity, for example, through the purchase of more efficient appliances. However, poor consumers may not have as much room to reduce their consumption when its price increases. The study found the short-run impacts of price changes on demand to be significant for all regions, at around -0.1, except for the EOA, which was insignificant. The irresponsiveness of demand in the EOA in the short run can be explained by the fact that changing consumption habits and decisions to buy new, more efficient appliances also takes time. The significant short-run price responses in the three other regions may be caused by lower-income consumers responding more quickly to sudden price increases by cutting any unnecessary usage. However, since their reductions in demand are within a narrow range, their response to price increases is evidently relatively small. The long-run results of this study are close to those of Atalla and Hunt (2016) and Hasanov et al. (2019). The short-run results are similar to the results of Atalla and Hunt (2016), Hasanov et al. (2019), and Al Dubyan and Gasim (2020).

The CDD impact is found to be significant for all regions, explained by the need for cooling in the Kingdom. The long-run CDD elasticity ranges from 0.27 to 0.75 across the regions, with the smallest elasticity in the EOA and the highest in the SOA, even though these regions are geographically close. This is because, although the average temperature (Table 1) in the WOA is higher than in the SOA, the higher impact of a one unit (%)

temperature increase in the SOA might be due to housing insulation. In the SOA, 33% of houses are old, compared with 22% in the WOA. In addition, 61% of housing in the WOA is apartments, compared with 30% in the SOA (GaStat 2018d). More apartments means a higher population density, which results in a smaller response of electricity consumption to increased cooling needs (Lariviere and Lafrance 1999). For the remaining two regions, the CDD elasticity in the COA is higher than in the EOA. This can be explained by the fact that the EOA region contains cooler cities in the north of the country, reducing its average CDD impact. The CDD elasticities are found to be statistically significant in all regions over the short run, following the same pattern as the long-run elasticities. Only two previous studies have used CDD data, Atalla and Hunt (2016), and Al Dubyan and Gasim (2020). Atalla and Hunt (2016) found the long-run and short-run CDD elasticities to be 0.16, while Al Dubyan and Gasim (2020) found them both to be 0.39. Since both studies results' are for national consumption, they are not directly comparable. However, our findings are close to those of Al Dubyan and Gasim (2020).

The impact of HDD is found to be significant only in the COA and EOA, with a higher impact in the EOA. This finding is expected because the weather data show that winters in the EOA (which includes the northern region), and the COA last longer than in the other two regions (NCEI-NOAA). Therefore, the use of heaters for longer periods may be necessary during the winter in the COA and EOA than in other regions. There is much less need for heating in the other two regions, hence their insignificant coefficients. Only Atalla and Hunt (2016) have previously investigated HDD as a driver of residential electricity consumption in the Kingdom. Their HDD elasticity finding of 0.50 is relatively high, considering the Kingdom's limited usage of heating during the winter.

We also tested the elasticities of demand drivers for variation over time and found no evidence for time-varying elasticities for the period investigated.

The study found the speed of adjustment (SoA) coefficients to be 0.48, 0.48, 0.38 and 0.57 for the COA, EOA, SOA and WOA, respectively. These SoA coefficients imply that it takes 2.1, 2.1, 2.6 and 1.8 years for the short-run deviations for the COA, EOA, SOA and WOA, respectively, to adjust back to equilibrium. The adjustment of half of the deviation takes 1.8, 1.8, 2.2 and 1.5 years, for the COA, EOA, SOA and WOA, respectively. These coefficients indicate the time it takes for regions to adjust to policy shocks and return to equilibrium. These findings align well with the UEDT measures. For example, the SOA region, which has inefficient consumption according to its estimated UEDT, takes the longest time to adjust. Given that the half-life of the SoA deviation is 2.2 years for the SOA, and the total adjustment takes 2.6 years, there is a 0.4-year room for an intervention from policymakers to encourage households to reduce their consumption. This can be mitigated by

policymakers promoting social awareness programs, among other forms of intervention.

We used the estimation results to perform decomposition analyses to reveal the contribution of each driver of residential electricity consumption across regions and time periods. The contributions of the different drivers will be discussed in more detail below. As can be seen from Figure 7, which visualizes the price effect, price changes did not significantly contribute to changes in electricity demand in physical (absolute) terms throughout the period in question, because electricity prices were largely fixed. The impact of prices started to be seen after 2015. In 2015 in the EOA, there was a substantial drop in demand compared with previous years. In 2016, the first phase of energy price reforms was introduced. Consumers in the EOA and COA showed stronger responses to the energy price reforms than in the other regions, with the largest response observed in the EOA, followed by the COA. The responses in the other two regions were smaller and almost identical.

Figure 7. Demand responses to price changes (price effect*) across regions and time periods.

Note: *Price effect = the contribution of price changes to demand changes; TWh - terrawatt-hours.

Source: Authors' calculation, based on estimated parameters.

8. Discussion of the Findings

These findings match the historical demand behavior depicted in Figure 4. All regions had a positive demand response in 2017 because there was no price increase during that year (the electricity price actually declined in real terms due to inflation). This implies that declining prices increased consumption. Higher prices in 2018, with the second wave of price reforms, produced negative demand responses in all regions. The responses in all regions in 2018 were substantially more pronounced than their historical averages. The greatest response was in the COA region, followed by the EOA. This finding is supported by the historical residential electricity

demand growth path illustrated in Figure 4.

Figure 8 presents regional UEDTs. The UEDT, which can be interpreted as the sum of the result of technological improvements and efficiency gains, has been improving in the WOA and EOA since 2013, indicating their relatively efficient use of electricity compared with the other regions. The UEDT in the SOA has always increased, due to it being the least populated region (Table 1) and, as a result, using the same amount of electricity for fewer services. The SOA's UEDT became smoother near the end of the estimation period.

Figure 8. Regional UEDTs.

Source: Authors' estimation results.

The COA's UEDT started to decline in recent years. The WOA and EOA showed some improvements in their UEDT, but they were not substantial.

Figures 9-12 show the regional impacts of electricity demand drivers for different years. The results are discussed for the last few years of the analysis, as these years are the most relevant for policymakers. The increase in electricity demand in the COA (Figure 9) in 2015 was mainly driven by inefficient consumption (UEDT effect in Figure 8). In 2016, when the first wave of the price reforms took place, and the region experienced a marked increase in prices, there were substantial efficiency gains for the first time since 2010, resulting from cuts in

unnecessary consumption. As Choe (1981), among others, discusses, an increase in energy prices could stimulate energy saving measures. The COA's efficiency improvements in 2016 reduced electricity consumption by 2.2% (Figure 4). In 2017, total electricity consumption increased. This was mainly driven by wider temperature variations during this year. However, there were again small efficiency gains and cuts in electricity consumption during this year, which were mainly the result of falling income. In 2018, after the second wave of fuel price reform, the COA experienced the largest decline in its consumption (-10.7%), mainly driven by the price effect. The efficiency gains for the COA in 2018 were smaller than in 2017.

Figure 9. Decomposition results for the COA.

Source: Authors' calculations based on estimated parameters.

There was a minor reduction in electricity consumption in the EOA (Figure 10) in 2015 due to the price effect and energy efficiency improvements. However, overall electricity consumption increased, driven by population and weather effects. The EOA's

consumption growth was smaller in 2015 than in 2014. Increased electricity prices, following the first wave of the price reform in 2016, were mainly responsible for reduced consumption during that year. Efficiency improvements also contributed to this

8. Discussion of the Findings

reduction. In 2017, the EOA's electricity consumption increased, and there were also some efficiency gains during this year. In 2018, the decline in electricity consumption more than halved compared with 2016. This reduction was mainly driven by the substantial price increases during this year.

There was an increase in electricity consumption in the SOA in 2015 (Figure 11). This was driven by the income effect and inefficient energy use. The later effect continued in the following years. Unlike the COA and EOA, there was no decline in consumption in 2016; rather, it increased by 3.5%, mainly driven by rising incomes. However, in 2017 the growth declined due to falling incomes. The SOA's electricity consumption declined for the first time in 2018 by 8.1% (1.4 TWh) due to the second wave of the price reform. The UEDT effect shows that the SOA has the least efficient residential electricity consumption of all the regions.

The growth in electricity consumption in the WOA

(Figure 12) slowed in 2015 due to substantial efficiency improvements also implemented during this year. However, electricity consumption in 2015 was still higher than in 2014, due to rising incomes. In 2016, electricity consumption in the WOA decreased, as incomes decreased. The WOA was the only region that witnessed a decline in consumption in 2017, which was as a result of reduced income and increased efficiency measures. The decline in the WOA's consumption continued in 2018, this time caused by price increases, though the decline was not as large as that seen in COA and EOA regions.

These decomposition analysis results are supportive of the empirical findings relating to long- and short-run impacts/elasticities. In conclusion, the EOA is more responsive to price changes, while the WOA is more responsive to income changes. There were some efficiency improvements in all regions in the last few years of the analysis, with the smallest being in the SOA and the second smallest being in the EOA.

Figure 10. The results of decomposition analyses for the EOA.

Source: Authors' calculations based on estimated parameters.

Figure 11. The results of decomposition analyses for the SOA.

Source: Authors' calculation based on estimated parameters.

Figure 12. The results of decomposition analyses for the WOA.

Source: Authors' calculation based on estimated parameters.

9. Conclusion and Policy Insights

This paper estimates the impact of price, income, and weather conditions on residential electricity consumption. It uses structural time series modeling to estimate the short- and long-run elasticities for the SEC's four operating regions in Saudi Arabia.

The findings shed light on the regional drivers of residential electricity demand in Saudi Arabia. The same set of explanatory variables influences residential electricity demand in each region. However, their influences vary by region. In 2016 and 2018, the Kingdom increased electricity prices to encourage greater energy efficiency. Overall, the implementation of the energy price reform, with a support package for lower-income households, was the right decision by the government to take to motivate rational energy consumption and increase its fiscal revenues, which could then be used to support long-term economic growth. Regions have separate paths to efficiency gains. Future price reforms alone might not be sufficient to promote further improvements in efficiency and reduce wasteful consumption. This study's empirical analyses concluded that, although all regions had some efficiency gains, there is still substantial room for improvement. The regional price and income responses to residential electricity consumption should be used to help design optimal household support policies. These elasticity figures can also help the policymakers to anticipate demand responses, and estimate the revenues they would get from future price reforms, more accurately, since each region will respond to such reforms differently. This would be useful for fiscal budgeting purposes.

The findings of this study show that the 2018 electricity price increase caused the largest consumption decline in physical units in the COA, the region with the smallest price elasticity. However, in percentage terms, the largest decline was found

in the EOA. This may be because EOA consumers, with higher income levels, already substantially adjusted their unnecessary consumption during the 2016 reforms, which was targeted at consumers with higher consumption profiles. Indeed, as our decomposition analyses revealed, the EOA had the largest decline in consumption in 2016, which was driven by price increases. These findings show why region-specific features need to be considered in order to make optimal policy decisions. Following the two waves of price reforms, the share of households consuming above 6,000 kWh per month decreased from 30% before 2016 to 18% after 2018. Households consuming less than 4,000 kWh per month increased from 52% before 2016 to 65% after 2018, which was mainly driven by the price increases. Put differently, the 2016 price reforms were successful in targeting and reducing electricity consumption in the richer regions, namely the EOA and COA. The declines in consumption in these regions were driven by price increases, with the EOA displaying the largest fall in consumption, followed by the COA. In the other two regions, the response to the price increases was much more limited. The second wave of price reform in 2018 targeted all consumers and was also successful in manifesting a price-driven reduction in electricity consumption. The highest impact was observed in the COA, while the three other regions experienced similar falls in consumption.

The full speed of adjustment and the half-life spread is significant for all regions. The spread between the total time to adjustment and the half-life indicates that there is room for policymakers to intervene. A multitude of intervention schemes might be useful. Many options could have a significant impact on consumption, particularly those that engage in the psychology of consumption, such as social awareness initiatives. Wasteful consumption (i.e., unnecessary use) negatively affects consumers due to its environmental impact, and policies could

be considered to promote social awareness of this fact. For instance, smart meters offer consumers the ability to adjust their habits by monitoring their energy use and supplying them with the data. Suppliers can use smart meters to allow consumers to compare their energy use with that of other consumers. Smart meters could also help consumers to identify inefficient appliances. Policymakers might consider deploying strategies to promote the use of efficient appliances in parallel with price reforms. This could be done in collaboration with private sector entities to promote the replacement of less efficient appliances, such as fridges, heaters, lighting systems, among others, with highly efficient ones. The Saudi Energy Efficiency Center's High Efficiency AC Initiative campaign has already been successful in this regard. The government could also issue soft and long-term loans for households who want to acquire energy efficient appliances. Another strategy would be to establish awareness programs about the environmental and financial benefits of transitioning to renewable energy. As the energy price reform develops, the government may wish to think about

differentiating price increases and support packages according to income and region, as different income groups and different regions react to electricity price changes differently.

Moreover, the population densities of the four regions suggest there is room for government intervention. Empirical studies (Lariviere and Lafrance [1999], among others) have shown that higher population density reduces electricity consumption, which urban planners should take into account. For instance, this explains why low population-dense regions like the SOA did not experience efficiency gains. The SOA is also the region with the highest share of older houses (33%), which are less likely to be energy efficient. This point should be taken into account in future city expansion plans to ensure sustainable energy consumption.

The benefit of price-related policies would most likely be increased if they were followed by policies focused on consumer behavior, such as rewarding citizens that consume within the lower range of electricity use for similar household types.

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Appendix 1

Table A1. Detailed estimation results.

Regions/ parameters	α_1	β_0	β_1	γ_0	γ_1	δ_0	δ_1	ϑ_0	ϑ_1	SoA			
COA	0.48***	-	0.23*	-0.10**	-	0.26**		0.08**		-0.48***			
EOA	0.48***	0.14**	-	-	-0.24**	0.14***		0.12***		-0.48***			
SOA	0.38***	-	0.34**	-0.15**	-	0.46**	-	-	-	-0.38***			
WOA	0.57***	0.43**	-	-0.10*	-	0.28*	-	-	-	-0.57***			
	Variances of disturbances ^a					Diagnostics summary						Model's data fit quality	
		level	slope	irregular			Normality	H(6)	Q(5,3)	r(1)	r(5)	Prediction error variance	R ²
COA	value	3.7e-04	2.6e-05	1.7e-04		Test value	0.081	0.628	5.124	-0.068	0.058	0.000	0.912
	q-ratio	1.000	0.069	0.459		p-value	0.961	0.707	0.401	aa	aa		
EOA	value	0.000	7.8e-05	3.3e-04		Test value	0.298	1.457	2.255	-0.187	-0.115	0.000	0.903
	q-ratio	0.000	0.234	1.000		p-value	0.226	0.345	0.813	aa	aa		
SOA	value	0.000	3.7e-05	1.4e-04		Test value	0.371	0.703	2.689	-0.028	-0.025	0.002	0.683
	q-ratio	0.000	0.027	1.000		p-value	0.831	0.674	0.748	aa	aa		
WOA	value	0.002	0.000	0.000		Test value	0.179	0.534	6.634	-0.177	-0.134	0.001	0.876
	q-ratio	1.000	0.000	0.000		p-value	0.914	0.768	0.249	aa	aa		

Notes: “-” = the coefficient is found to be insignificant, and the appropriate term is excluded from the specification; “***” = significance of the coefficient at 1% significant level; ^a if the variance of the component is zero it means the component is constant over time; normality stands for the Jarque–Bera (Jargue and Bera 1980, 1981, 1987) goodness-of-fit test for testing the normality; H(k) stands for the heteroscedasticity test of residuals; Q(q,q-p) is the Ljung–Box Q test (Ljung and Box 1978) for autocorrelations; r(10) is the Lagrange multiplier test for serial correlation (Harvey 1981); aa = the Lagrange multiplier tests confidence interval (-0.371, 0.371), based on the number of observations. The following dummy variables are used accordingly: COA: pulse dummy for 1993 and 2015, step dummy for 2000; EOA: step dummy for 1999 and pulse dummy for 2011; SOA: pulse dummy for 2009; WOA: pulse dummies for 1992, 1998 and 2011.

Notes

A green geometric graphic consisting of several overlapping triangles and polygons, located in the top-left corner of the page.

Notes

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About the Project

The objective of the KAPSARC Global Energy Macroeconometric Model (KGEMM) project is to develop a domestic policy analysis tool that examines the impacts of domestic policy measures and global economic and energy shocks on the Kingdom of Saudi Arabia. Commonly available models are typically more focused on the global economy (and the major contributors to global GDP). They often use an oversimplified representation of major oil and gas exporting economies, including Saudi Arabia, to capture global energy flows.

The project is guided by the following objectives:

- To provide a better representation of the Saudi economy than previous models by taking into account the stylized facts of the Saudi economy.
- To offer KAPSARC's research team and its stakeholders a macroeconometric model that is capable of evaluating the effects of different policy options (energy price reforms and fiscal policy changes, among others) on the Kingdom's economy. The model is also capable of analyzing the current status and future paths of macroeconomic and energy indicators.

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