Modeling and Projecting Regional Electricity Demand for Saudi Arabia

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We modeled the electricity demand for Saudi Arabia at a regional level. We used estimation techniques that allow the detection of exogenous interventions and stochastic parameters. Saudi Arabia's regions have unique responses to prices and income levels regarding electricity demand. The model can be used to simulate different policy scenarios. The model projects that electricity demand under moderate economic growth and no price changes for the Kingdom will be 366 TWh by 2030.
Summary

This paper utilizes a structural time series approach to model Saudi Arabia's regional electricity demand, capturing undetected forces of variability in the data-generating process that include improvements in technology, energy-saving behavior, and other underlying trends that are excluded under conventional estimation methods. National models of aggregate electricity consumption might not be representative, as electricity prices are administered regionally and Saudi Arabia’s regions have unique social and economic characteristics. We find evidence that the regions have unique responses to prices and income levels with regard to electricity demand.

Additionally, we use our estimated model to project the regional baseline demand for electricity for Saudi Arabia and create a scenario to demonstrate how a price increase would impact these regions differently. This information is valuable for policymakers in Saudi Arabia, as the fuel mix to generate electricity differs between regions. Our baseline electricity demand projections indicate that under the assumptions of moderate economic growth and no price changes, total electricity demand in Saudi Arabia will reach 366 TWh by 2030.
Modeling and Projecting Regional Electricity Demand for Saudi Arabia

Introduction

Modeling national aggregate electricity consumption might prevent Saudi Arabia’s situation from being reflected accurately. Saudi Arabia is a large country, occupying an estimated 2.15 million square kilometers. Saudi Arabia is typically characterized as having four regions with unique topographies, economies, and climates.

Electricity demand is generally driven by aggregate and disaggregate drivers that differ from region to region. These drivers include prices, weather, industrial and commercial activity, wealth, population, and income. Overall, electricity customers in Saudi Arabia can be grouped into six categories: residential, commercial, government, industrial, agricultural, and others. Each region in Saudi Arabia constitutes a share of these customers, and Figure 1 highlights the share distribution of customers for each region. For most regions, residential electricity consumption accounts for approximately 50%–60% of total electricity consumption (ECRA 2020). In the Eastern region, in contrast, this share is close to 30%. The Eastern region has a significant industrial presence, being close to oil and gas extraction fields and supported by complementary industries that have been set up over many decades.

Several papers have highlighted the differences in electricity consumption by customer type between regions. Mikayilov et al. (2020b) found heterogeneous regional drivers of residential electricity demand. Specifically, the response to price, income, and weather is specific to each region. These authors showed that regions vary in electricity consumption with respect to their incomes and that during electricity price reform (EPR) periods, residential electricity consumption has reacted differently in each region. Moreover, their paper mentioned other characteristics such as differences in preferences on the distribution of housing types in each region and overall regional density. The authors reported regional income and

Figure 1. Electricity Consumption by Customer Type in Saudi Arabia.

Source: ECRA reports, various issues.
price elasticities from 1990–2018. For example, the (poorer) Western and Southern regions are more susceptible to income changes, with their income elasticities found to be 1.02 and 0.54, respectively. However, the income elasticities are lowest in the prosperous regions (0.44 for the Central and 0.27 for the Eastern region). The responses of the regions to price variations also vary, with the Eastern region's price elasticity being the highest.

Another study that considered regional heterogeneity in industrial electricity consumption in Saudi Arabia found that industrial concentration exhibits excessive variation among regions (Mikayilov et al. 2022). The authors provided evidence of profound disparities in industrial electricity consumption among the regions in Saudi Arabia; for example, 72% of all electricity consumed by the industrial sector corresponded to the Eastern region in 2019. In the Southern region, in contrast, the share was close to 1%. The shares of the Central and Southern regions, in turn, were 14% and 13%, respectively. The authors found that income and price responses vary accordingly within regions due to the industrial sector's consumption level, size, and maturity. They reported the elasticities of income and price, proxied by industrial GDP and industrial electricity prices, to be the primary driver of industrial electricity consumption. The Southern region was found to have the highest response (1.06) to GDP increases, which intuitively reflects the state of the industrial sector in the south. However, in the regions with moderate and high industrialization levels, the elasticities to GDP range between 0.449 and 0.56. The price elasticities are also indicative of the maturity of the industrial presence within regions. Regions with advanced industrialization are not as affected by price changes as less developed regions. The Southern region reacts more severely (-0.249% to -0.147%) to every 1% change in price. More mature regions, such as the Eastern (-0.021% to -0.06%) and Central (-0.17%) regions, are less impacted.

This paper draws parallels with previous studies on Saudi Arabia's regional electricity consumption. However, it considers new techniques and aggregate data on all electricity customers to give policymakers an overarching view of the total regional response to changes in income and prices. Additionally, projecting electricity demand and understanding the demand response at the regional level are beneficial to policymakers from the supply side. Since generation sources differ significantly by region (see Figure 2), regional demand projection can offer perspective on the system costs and capacity planning needs associated with a projected demand scenario.

The methodology in this paper formalizes the regional modeling approach and builds scenarios to project electricity consumption on a regional basis in Saudi Arabia based on changes in income and prices. Our work contributes to the literature on regional electricity modeling in Saudi Arabia in the following ways. First, our methodology leverages the general-to-specific modeling approach utilizing a multipath-search machine learning algorithm and structural time series modeling (STSM), which captures undetected forces of variability in the data-generating process that include improvements in technology, energy-saving behavior, and other underlying trends that can be excluded under conventional estimation methods. Second, we project regional total electricity demand to 2030 under different price scenarios and GDP growth trajectories. Third, the paper gives policymakers and associated generation companies a reference on anticipated demand based on changing drivers of electricity use as Saudi Arabia implements its Vision 2030 agenda.

Introduction
Figure 2. Fuel mix by region, 2015–2019.

Source: Various ECRA reports.
This section reviews papers devoted to forecasting/projecting electricity demand at the regional level for Saudi Arabia. We are aware of only one recent study, Mikayilov et al. (2020a), dedicated to total electricity demand modeling for the Saudi Arabian case at a regional level. Diabi (1998) also modeled regional demand; however, he used data for the 1980–1992 period, which today would not represent the focal relationships well, considering the time that has passed. Moreover, to our knowledge, no published works are focused on projecting total electricity demand at either the Kingdom or the regional level by means of econometric techniques. Soummane and Ghersi (2022) employed a computable general equilibrium model and made sector-level and total electricity demand projections up to 2030. They did not deal with regional electricity demand behaviors. Soummane and Ghersi (2022) projected total electricity demand to be 365.4 TWh and 324.9 TWh in their reference and energy efficiency scenarios, respectively. Soummane (2021) analyzed the historical behavior of electricity demand in Saudi Arabia from 1970 to 2018. Mikayilov et al. (2020b) and Mikayilov et al. (2021) explored region-specific residential and industrial demand behaviors, not total numbers. Utilizing a 1990–2016 data sample, Mikayilov et al. (2020a) modeled region-level total electricity demand for Saudi Arabia. Unlike us, however, first, they did not perform projection exercises. Second, their data set included only one observation corresponding the period after the energy governance policies took effect. This, in turn, might have limited the information needed to achieve the actual parameters of relationships. Darandary et al. (2022) used the findings of Mikayilov et al. (2020a) and estimated the total cost savings and total avoided carbon emissions from reduced residential electricity demand, utilizing counterfactual scenario analyses. However, Darandary et al. (2022) made no projections on region-specific electricity demand values. Hence, in view of the ongoing energy-related governance strategies being followed by the Kingdom and of energy policies worldwide, it is worth modeling and making projections at a regional level, considering the region-specific features of demand and current strategies.

Theoretical Framework

We utilize the conventional demand-side modeling approach, as in Maddala et al. (1997), Amarawickrama and Hunt (2005), and Hasanov et al. (2017), among others, and define per capita electricity demand as a function of real per capita income, the real electricity price and weather conditions. Mathematically, the demand function is expressed as follows:

\[ \text{dele} = f(\text{inc}, p, cdd, hdd) \]  \hspace{1cm} (1)

where electricity demand per capita (dele) is defined as a function of per capita real income (inc), the electricity price in real terms (p), and cooling degree days (cdd) and heating degree days (hdd), representing weather variables. All variables in equation (1) are expressed in logarithmic form. Since the derivation of energy-demand models is discussed and reviewed in several papers, including Nordhaus (1977), Beenstock and Dalziel (1986), Huntington et al. (2019), and Hasanov and Mikayilov (2020), inter alia, we will not detail the derivation of the model specification used. Interested readers can refer to the provided references for the detailed derivations.

In addition to explicit drivers (such as income and price) of energy demand, we consider exogenous channels of impact, such as technological improvements, through the utilized econometric approaches. Namely, the STSM approach (Harvey 1989) is used as an additional estimation technique
that allows the trend of the relationship to be treated as stochastic in testing. This stochastic trend, which is a general case of the conventional deterministic trend, is a better representation of changes in exogenous factors such as technological improvements (Hunt et al. [2000], among others). Moreover, the STSM approach allows us to consider the potential time variation in the parameters of the relationship (Harvey 1989). Furthermore, the potential impact of exogenous factors is investigated through the Autometrics machine learning algorithm (Hendry and Doornik [2014], among others). This algorithm enables detection of intervention dummies and broken trend dummies and could be considered to offer an alternative to the use of the stochastic trend in the STSM approach.

Data

We utilize annual data from 1990 to 2019 due to data availability. Our dependent variable is region-specific total electricity consumption in megawatt-hours (MWh). Electricity consumption is expressed in per capita terms using regional population data. Electricity demand data are retrieved from the Saudi Electricity Company (SEC) and SEC via Saudi Arabian Monetary Authority Annual Statistics (SAMA 2020).

The regional population numbers are derived from the population surveys for the 1990–2006 period of the General Authority for Statistics of Saudi Arabia. For the years from 2007 to 2019, they are retrieved from SAMA (2020), where data are available for thirteen administrative provinces.

We utilize two different income proxies with region-specific features. Namely, nonoil gross value added (GVA) of Saudi Arabia is used to proxy income for the Central, Southern, and Western regions. The rationale for using nonoil GVA for these three regions is that these regions’ economies are not specialized in oil. Overall GDP, which includes oil and nonoil activities, might not be representative of economic activity for those regions, and aggregate data might thus cloud our analysis of the relationships of interest. In the Eastern region, where oil is the main component of the economy, the overall GDP of the Kingdom is used as an income proxy. GDP and nonoil GVA are in a million Saudi riyals at constant 2010 prices and are sourced from SAMA (2020). Both GDP and nonoil GDP are expressed in per capita terms, dividing the total numbers by the total population of the Kingdom.

Price is represented by the weighted electricity price, calculated for each region, in Saudi riyals per kWh. The region-specific consumption numbers by consumer type are used as weights. Different consumer-specific (residential, industrial, commercial, government, and agricultural) price numbers are used to calculate the weighted prices. The fact that the share of electricity consumption changes across regions and time by consumer type (for example, in the Central, Western, and Southern regions, the main share corresponds to residential consumption, at 51%, 56%, and 70%, respectively, while in the Eastern region, it corresponds to industrial consumption, at 51%) is thereby accounted for in the region-specific price calculations. The price deflator is a weighted average of deflators for nonoil manufacturing and oil refining, and the corresponding shares of GVAs are used as weights. For the other three regions, the industrial price deflator is used to deflate the industrial electricity price.

We also used cooling degree days (cdd) and heating degree days (hdd) data to control the temperature impact. The cdd and hdd data are taken from Mikayilov et al. (2021).
Econometric Methodology

We follow the methodology of the time series framework in terms of testing first for unit roots in the variable series and then for the existence of cointegration relationships. The augmented Dickey–Fuller test (Dickey and Fuller 1981) assesses the variables’ unit-root properties. The presence of cointegration relationships among the variables is tested using the cointegration test proposed by Banerjee et al. (1993) and Banerjee et al. (1998). To assess the potential nonlinearity in parameters, in addition to the conventional Ramsey RESET test (Ramsey 1969) and a general test for heteroscedasticity (White 1980), we use the nonlinearity test proposed by Castle and Hendry (2010). The parameters are also treated to vary over time and are tested for potential variation under the STSM framework (Harvey 1989).

To model the relationships among the variables, we utilize the general-to-specific (Gets) modeling approach (see Hendry and Doornik [2014], among others). First, a general unrestricted model (GUM), which includes all the relevant variables, is formed in Gets. The Gets approach is implemented by means of the so-called Autometrics multipath-search machine learning algorithm (Doornik and Hendry [2018], among others). Autometrics enables identification of potential interventions such as one-time pulses, blips, changes in levels, and trend breaks through impulse-indicator saturation (IIS), differenced impulse-indicator saturation (DIS), step-indicator saturation (SIS) and trend-indicator saturation (TES) dummies. It also tests parameters for a potential varying nature over time via the so-called multiplicative-indicator saturation approach (Ericsson 2012; Castle et al. 2017; Castle and Hendry 2019). In this research, we utilize all the abovementioned features of the Autometrics algorithm.

The general functional specification used in the empirical estimations is as follows:

\[
delet_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i \delet_{t-i} + \sum_{i=1}^{2} \beta_i \inc_{t-i} + \sum_{i=1}^{2} \gamma_i \p_{t-i} + \sum_{i=1}^{2} \delta_i \cdd_{t-i} + \sum_{i=1}^{2} \theta_i \hdd_{t-i} + \sum_{i=1}^{3} \var_i \IIS_i + \sum_{i=1}^{3} \psi_i \SIS_i + \sum_{i=1}^{3} \varphi_i \DIIS_i + \sum_{i=1}^{3} \omega_i \TIS_i + \epsilon_t \# \]

where \( \delet \) is the region-specific per capita electricity demand, \( \inc \) is per capita income, \( \p \) is the electricity price, \( \cdd \) is cooling degree days, and \( \hdd \) is heating degree days. All variables are expressed in logarithmic form. \( T \) is the number of observations. IIS, SIS, DIIS, and TIS represent the impulse indicator saturation, step indicator saturation, differenced impulse indicator saturation, and trend indicator saturation dummies. Following the methodology of the Gets approach, first, all the theory-related variables with two lags are held fixed, and the intervention dummies are chosen based on the tight significance level. In the second step fixing the chosen dummies, the final model is determined based on the battery of diagnostic tests. The multipath selection procedure is performed with the PcGive econometric modeling program (Doornik and Hendry 2018).

Empirical Estimation Results

Following the roadmap in the methodology section, first, we assess the unit-root properties of the variables. The detailed results of the unit-root tests are shown in Table 1.

The test results show that all variables are integrated of the first order; in other words, their first differences are stationary. Having established that the integration order is the same across the variables, we test for the existence of a long-run relationship by employing the cointegration test proposed by Banerjee et al. (1993), inter alia. Table 2 provides the results of these exercises.
The cointegration test points to the existence of a long-run relationship for all the regions. Considering the presence of the long-run relationship, we utilize the Autometrics algorithm for model selection under the Gets framework. In doing so, initially, we estimate the relationship with two lags, using the general specification as in equation (2). Then, we select the final model by employing the multipath search procedure.

Table 3 demonstrates the diagnostic test results. All the diagnostic results favor the found models, as evident from the table.

Table 1. Unit-root test results.

<table>
<thead>
<tr>
<th></th>
<th>Dele</th>
<th>p</th>
<th>Inc</th>
<th>Cdd</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level</td>
<td>Differenced</td>
<td>Level</td>
<td>Differenced</td>
</tr>
<tr>
<td>COA</td>
<td>-2.2791</td>
<td>-3.2534**</td>
<td>-1.9281</td>
<td>-5.8197***</td>
</tr>
<tr>
<td>EOA</td>
<td>-0.4388</td>
<td>-4.1998***</td>
<td>-1.8688</td>
<td>-5.6433***</td>
</tr>
<tr>
<td>SOA</td>
<td>-1.5118</td>
<td>-4.4538***</td>
<td>-1.8985</td>
<td>-5.6310***</td>
</tr>
<tr>
<td>WOA</td>
<td>-2.1568</td>
<td>-5.0827***</td>
<td>-1.4702</td>
<td>-5.1164***</td>
</tr>
</tbody>
</table>

Notes: All variables are as defined in the methodology section; ***, **, and * stand for rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively; ξ = the income proxy for SOA and WOA is the same as that for COA, and hence, the test is not repeated.

Source: Estimation results.

Table 2. Cointegration test results.

<table>
<thead>
<tr>
<th></th>
<th>COA</th>
<th>EOA</th>
<th>SOA</th>
<th>WOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test statistics</td>
<td>-5.4605**</td>
<td>-4.9703*</td>
<td>-4.1403*</td>
<td>-4.9442*</td>
</tr>
</tbody>
</table>

Notes: Null hypothesis of the test states no cointegration; ** and * stand for rejection of the null hypothesis at the 5% and 10% significance levels, respectively.

Source: Estimation results.

Table 3. Outcomes of diagnostic tests.

<table>
<thead>
<tr>
<th></th>
<th>COA</th>
<th>EOA</th>
<th>SOA</th>
<th>WOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR 1-2 test</td>
<td>0.42829 [0.6575]</td>
<td>0.18192 [0.8350]</td>
<td>1.7460 [0.1989]</td>
<td>0.9627 [0.4017]</td>
</tr>
<tr>
<td>ARCH 1-1 test</td>
<td>0.16751 [0.6856]</td>
<td>0.75195 [0.3935]</td>
<td>0.52711 [0.4741]</td>
<td>0.0160 [0.9005]</td>
</tr>
<tr>
<td>Normality test</td>
<td>1.0603 [0.5885]</td>
<td>0.61395 [0.7357]</td>
<td>1.1144 [0.5728]</td>
<td>1.4115 [0.4937]</td>
</tr>
<tr>
<td>Hetero test</td>
<td>1.0060 [0.4800]</td>
<td>1.3060 [0.2984]</td>
<td>1.8512 [0.1291]</td>
<td>0.8130 [0.6427]</td>
</tr>
<tr>
<td>RESET23 test</td>
<td>0.52420 [0.5999]</td>
<td>0.38451 [0.6857]</td>
<td>2.1909 [0.1367]</td>
<td>0.9593 [0.4030]</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.996</td>
<td>0.989</td>
<td>0.997</td>
<td>0.997</td>
</tr>
</tbody>
</table>

Notes: AR = autocorrelation test (Godfrey 1978); ARCH = autoregressive conditional heteroscedasticity test (Engle 1982); Normality test = Doornik and Hansen (1994) normality test; Hetero test = heteroscedasticity test (White 1980); RESET23 = regression specification test (Ramsey 1969). p values are in parentheses.

Source: Estimation results.
Table 4 outlines the region-specific long-run and short-run elasticities. The complete picture of the estimation results is given in Appendix A1.

The outcomes of the nonlinearity tests (Castle and Hendry 2010) are portrayed in Table 5. These tests make use of various nonlinear combinations of the variables and assess nonlinearity through F and chi-square tests. The null hypothesis of the tests states the linearity of the parameters. The tests do not confirm the existence of nonlinearity, as the results in Table 5 demonstrate.

In addition, we estimate the relationships among the variables of interest using dynamic ordinary least squares (Saikkonen 1992; Stock and Watson 1993) and STSM (Harvey 1989) and the autoregressive distributed lag (ARDL; Pesaran and Shin 1999; Pesaran et al. 2001) method as a robustness check, the findings of which are displayed in Appendices 2 and 3. The results show that these models’ findings are closer to the Autometrics output. We also utilize the STSM methodology to examine the time variation in the parameters and test whether the relationship incorporates a stochastic trend. The estimation results offer no evidence of varying parameters and stochastic trends in any region. In other words, the STSM results support the findings of nonlinearity tests in the Gets approach. This also substantiates the usage of the Gets approach, where the parameters are treated as constant over time.

### Discussion of the Empirical Findings

Our region-specific estimation of electricity demand behavior indicates that the main drivers of electricity use are income and price. According to the

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**Table 4. Short- and long-run estimation results.**

<table>
<thead>
<tr>
<th></th>
<th>COA</th>
<th>EOA</th>
<th>SOA</th>
<th>WOA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sh-run</td>
<td>long-run</td>
<td>sh-run</td>
<td>long run</td>
</tr>
<tr>
<td>inc</td>
<td>-</td>
<td>0.535***</td>
<td>0.334***</td>
<td>0.554**</td>
</tr>
<tr>
<td>p</td>
<td>-0.087*</td>
<td>-0.461***</td>
<td>-</td>
<td>-1.88*</td>
</tr>
<tr>
<td>cdd</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes: sh-run = short-run elasticity; long-run = long-run elasticity; inc = income, p = price, cdd = cooling degree days; “*” no short-run impact; “**” and “***” stand for rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. Source: Estimation results.

**Table 5. Nonlinearity test results.**

<table>
<thead>
<tr>
<th></th>
<th>COA</th>
<th>EOA</th>
<th>SOA</th>
<th>WOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index test (F form)</td>
<td>1.3666 [0.3001]</td>
<td>2.1964 [0.0989]</td>
<td>0.91619 [0.5611]</td>
<td>0.38005 [0.7037]</td>
</tr>
<tr>
<td>Core index test (F form)</td>
<td>0.67683 [0.7277]</td>
<td>0.43110 [0.9041]</td>
<td>1.6774 [0.2002]</td>
<td>0.3268 [0.9111]</td>
</tr>
</tbody>
</table>

Notes: The null hypothesis of both tests states linearity of the parameters; p values are in parentheses. Source: Estimation results.
estimation results, the demand responses to price and income vary across regions. In line with the findings of previous literature (Chang et al. [2014], among others), we find that the impact of income is higher in the less established Southern region. The price impact is found to be smaller in the more affluent Eastern region. The smaller price response to demand in the Eastern region can be interpreted as indicative of the fact that industrial consumers account for a substantial portion of the region’s electricity consumption. In the other three regions, in contrast, the main consumption share corresponds to residential consumers. Electricity demand among industrial consumers in the Eastern region is less responsive to price than that among residential consumers (Mikayilov et al. 2020b, 2021). This smaller response of industrial than of residential consumers might be explained by the potential for more agile behavioral change among the latter. In addition, the industrial sector in the Eastern region has government support due to its unique role in the country. Hence, the smaller price response of overall electricity demand in the region is rational.

For COA and WOA, the estimated income elasticities are close in magnitude to the estimates of Mikayilov et al. (2020a). However, for EOA and SOA, our elasticities are larger than their results. This distinction may well result from various factors. First, the authorities have updated the historical income data that we use, utilizing new approaches and more rigorous data-related methodologies. This, in turn, results in a change in the behavior of the income proxy, potentially resulting in a shift in demand response. Furthermore, Mikayilov et al.’s (2020a) data period ends in 2016 and thus their sample captures to a lesser extent information related to the ongoing energy price governance strategy developments of recent years. Additionally, Mikayilov et al. (2020a) utilized disposable income as an income proxy for the Eastern region. Disposable income is articulated such that it is representative of residential consumers’ income behavior. The Eastern region accounts for approximately 30% of all consumption, and its disposable income level does not capture the demand characteristics of the major consumer type there, the industrial sector. The weather indicator is found to have a statistically significant impact only in the Western region. This can be interpreted with reference to the region’s specific characteristics, such as the fact that it is the hottest region and correspondingly shows the highest residential electricity consumption (Mikayilov et al. 2020b).

Assumptions for Demand Projections

Utilizing the estimated regional electricity demand models, we aim to make demand projections for 2030. For this purpose, two scenarios are employed. In the first scenario (business-as-usual, BaU hereafter), prices are fixed at their 2021 values. The assumptions for total and nonoil GDP, population, and the price deflators are articulated based on Oxford Economics’s 1 March 2022 release (Oxford Economics 2022). The region-specific population numbers for the forecast horizon are calculated from total population values and average historical regional shares. Based on the historical data, the average population shares for COA, EOA, SOA, and WOA are 32%, 18%, 14%, and 36%, respectively. For the second scenario (Rise), all other assumptions are the same as in the BaU case. For the Rise scenario, all sector-specific prices increase by 5% each year starting from 2023. The assumptions for the projection exercises are described in Table 6.
Projection Results and Discussion

The output projections for electricity demand utilizing the estimated models under the partial equilibrium framework and the associated assumptions for the two scenarios are presented in Figure 3. As seen from the two scenario results in Figure 3, the annual 5% price increase results in a 126 TWh decline in demand at the Kingdom level for the 2023–2030 period, equaling 16 TWh per annum. In addition, the increase reduces consumption by 34 TWh for 2030 alone, which amounts to the Southern region’s annual demand need. At the region level, the overall reduction numbers for COA, EOA, SOA, and WOA are 55 TWh, 21 TWh, 14 TWh, and 35 TWh, respectively, for the same 8-year period. Of course, we are not comparing the optimal pricing scenario but rather are comparing only the demand differences in the two different scenarios. Independent research could take up the research question of what the optimal pricing scheme/trajectory is. In addition, the scenarios are articulated for methodological purposes to present the estimated models’ forecasting/projection features. Hence, the projection exercises can be considered a policy simulation utilizing the set assumptions. Considering the ongoing energy price governance policy developments and the targets set by the government, such as a shift to a 50–50 natural gas and renewables share in power generation, the Saudi Green Initiative, and Giga projects, among others, we are likely to see some behavioral changes in the trajectory of electricity demand at both the region and Kingdom levels. However, the impact of developments and possibilities such as the ones mentioned above on projected demand numbers could be considered if information on policy targets or designs is available to the policymaker. Hence, the proposed region-specific model tool enables energy strategists to make demand projections and policy simulations based on targeted scenarios.
Figure 3. Projection results

A

Regional and total electricity demand (BaU)

Source: Forecasting results

B

Regional and total electricity demand (5% price increase scenario)

Source: Forecasting results
Conclusion

This paper draws parallels with previous studies on Saudi Arabia’s regional electricity consumption and considers new techniques and aggregate data on all electricity customers. We conduct a region-specific estimation of electricity demand behavior and conclude that the main drivers of electricity use are income and price. Our estimation finds that responses to price and income changes vary across regions in Saudi Arabia. Regions considered more developed are found to be least responsive to income changes, in line with expectations. In contrast, income plays a larger role in electricity demand in developing regions such as the Southern region. The price elasticities of demand by region are also heterogeneous. The Eastern region is least responsive and the Central region most responsive to price changes. These differences allow us to project future scenarios to showcase how aggregate drivers such as income and prices alter electricity demand paths.

Two scenarios are employed for the projection exercise. The BaU scenario assumes that prices are fixed at their 2021 values, and another scenario assumes that prices will rise by 5% year-on-year from 2023 to 2030. Under these assumptions, total electricity consumption would amount to 365 TWh in 2030 under the baseline scenario and to 332 TWh under the rising price scenario. However, consideration of the differential regional contributions between the two scenarios reveals varying consumption paths. The Western region’s total electricity consumption would be 21% higher in 2030 relative to that in the no-price change case, whereas the Central region would see only an 8% difference during the period. The Eastern and Western regions would see their electricity use grow by 14% and 13%, respectively.

To give policymakers a representative view of the total regional response to changes in income and prices, regional modeling approaches should be applied. Regions have unique social and economic characteristics that differentiate them from each other and, in turn, their responses to electricity consumption drivers. All electricity is not created equal, and generation sources differ significantly by region due to resource and capacity constraints. A regional demand projection approach gives perspective on the system costs and capacity planning needs associated with a projected demand scenario as Saudi Arabia nears 2030.
References


### Appendix A1. Detailed estimation results.

<table>
<thead>
<tr>
<th></th>
<th>Dele(-1)</th>
<th>p</th>
<th>p(-1)</th>
<th>Inc</th>
<th>Inc(-1)</th>
<th>Cdd</th>
<th>Cdd(-1)</th>
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<tbody>
<tr>
<td>COA</td>
<td>0.4545***</td>
<td>-0.0870*</td>
<td>-0.1644***</td>
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<td>0.2918**</td>
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<td>-</td>
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<td>EOA</td>
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<td>-0.1133**</td>
<td>0.3336**</td>
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<td>-</td>
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<tr>
<td>SOA</td>
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<td>-0.1407**</td>
<td>-</td>
<td>0.5396***</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>WOA</td>
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<td>0.0962**</td>
<td></td>
<td>0.2587**</td>
<td>-</td>
<td>0.2118*</td>
<td>-</td>
</tr>
</tbody>
</table>


Source: Estimation results.

### Appendix A2. Short- and long-run elasticities from the STSM approach.

<table>
<thead>
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<th>WOA</th>
<th>SOA</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Short-run</td>
<td>Long-run</td>
<td>Short-run</td>
<td>Long-run</td>
</tr>
<tr>
<td>Income</td>
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<td>0.695***</td>
<td>0.181*</td>
<td>0.233***</td>
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<td>Price</td>
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<td>-0.080***</td>
<td>-0.180***</td>
<td>-0.501***</td>
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</table>

Notes: "-" indicates no short-run impact; *, ** and *** stand for rejection of the null hypothesis at the 10%, 5% and 1% significance levels, respectively.

Source: Estimation results.

### Appendix A3. Long-run elasticities from DOLS and ARDL approaches.

<table>
<thead>
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<th>WOA</th>
<th>SOA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DOLS</td>
<td>ARDL</td>
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<td>ARDL</td>
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<td>Income</td>
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<td>0.532**</td>
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<tr>
<td>Price</td>
<td>-0.251**</td>
<td>-0.444***</td>
<td>-0.125*</td>
<td>-0.265**</td>
</tr>
</tbody>
</table>

Notes: "-" indicates no short-run impact; *, ** and *** stand for rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Source: Estimation results.
About the Authors

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About the Project

The Modeling Energy Consumption and its Impacts in Saudi Arabia project aims to conduct advisory and applied research activities focused on modeling and forecasting indicators of energy consumption and their impacts in Saudi Arabia. In line with the ongoing energy policies that the Kingdom is implementing, the project focuses on three main areas:

- Modeling and forecasting energy consumption indicators.
- Modeling and forecasting the environmental impacts of energy consumption.
- Investigating the trajectories and potential of energy efficiency.