Theoretical Framework for Industrial Electricity Consumption Revisited: Empirical Analysis and Projections for Saudi Arabia

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Key Points

This paper presents the following research outcomes:

It develops a theoretical framework in which demographic and economic factors such as price and income can be seen to jointly determine industrial energy consumption. We select the population aged between 15-64 as the demographic variable. For a robustness check, we also consider those aged 15 and over in the analysis.

The estimation of the framework for Saudi Arabia between 1984-2016 revealed that:

- There is a long run relationship between industrial electricity consumption and demographic and economic factors.
- A 1% increase in the population aged 15-64 increases industrial electricity consumption by 1% in the long-run. This also holds true for the control group aged 15 and over.
- Industrial electricity consumption is price inelastic with an elasticity of -0.1 in the long run.

Industrial electricity consumption is also income inelastic and the long-run elasticity varies between 0.2-0.3 depending on whether level or per-capita relationship is considered.

The projections for industrial electricity consumption extend to 2025 and show that future consumption will be more responsive to population growth than price increases.

Policymakers should expect that the energy price reform in Saudi Arabia will reduce industrial electricity consumption. However, this reduction will be slight as the price effect is found to be very small. At the same time, policymakers should be aware that the increasing population aged 15-64, and all those over 15, will lead to an increase in industrial electricity consumption. Lastly, the estimations show that industrial electricity consumption will fully absorb shocks including policy interventions in less than a year.

Summary

It is important to account for changes not only in economic factors but also in demographic factors in energy/electricity consumption. These changes should be measured explicitly in modeling and forecasting electricity consumption so that policymakers can decide to take these variables into account or to ignore them when formulating policy measures. Campbell (2018), among others, empirically shows that omitting demographic indicators in the analysis of industrial electricity consumption may cause upward bias in income and price elasticities, as demographic indicators can impact the consumption independent of income and price. However, the conventional energy demand framework usually measures the impacts of income and price and does not accommodate demographic effects. To overcome this, previous studies have augmented the conventional framework by including demographic indicators such as population, age groups and urbanization. However, many such studies concentrate either on total or on residential electricity consumption, and very few have investigated industrial electricity consumption. Additionally, most of these studies, and all studies focused on industrial electricity demand, do not provide a theoretical foundation for including the demographic variables that are of interest in the standard energy demand framework. Accordingly, this research reconsidered the conventional demand-side approach and developed a new framework in which industrial energy consumption is a function of both economic and demographic factors.

This framework can be applied to the consumption of electricity and other energy products in developed, developing and less developed countries. In our research, the framework was applied to industrial electricity consumption in Saudi Arabia for a number of reasons. First, the Kingdom has unique demographic characteristics: during 1984-2016, the average per annum growth rate of the population was

about 3%. The share of the population aged 15-64, one of the most important economic and societal demographic indicators, increased from 54.1% in 1984 to 68.8% in 2016 (UN 2018). Considering that demographic indicators usually change slowly over time, this change is substantial and has considerable implications for the country's energy consumption. Second, during 1984-2016, the share of industrial value added in the country's gross domestic product (GDP) was about 60.6%. Third, strategic development programs such as Saudi Vision 2030 (SV2030) consider industry as one of the main drivers of future economic growth. Fourth, SV2030, especially its Fiscal Balance Program, highlights the importance of energy price reform (EPR). Saudi Arabia's EPR aims to increase domestic energy prices to international reference levels to make its economy and society more efficient and to increase the government's budget revenues (FBP 2018). As domestic energy prices, including those for industry, were historically administered at a very low level by the government, the EPR will have an impact on industrial energy consumption. However, successful implementation of the EPR will also depend on understanding its impact on energy consumption and industry. This requires estimating how prices could affect energy consumption. Such estimations should provide policymakers with an understanding of the expected impact of the EPR, particularly on energy consumption and government revenues.

Despite the importance of industry in Saudi Arabia, there is very little research on the country's industrial electricity consumption. To the best of our knowledge, this is the first piece of research to examine both the demographic and economic aspects of industrial electricity demand.

To achieve more robust results, we employed different unit root and cointegration tests, and long-run estimation methods. We also used two

different specifications in estimating long-run elasticities of the industrial electricity consumption. Our conclusions from the empirical analysis can be summarized as follows:

Both demographic — population aged 15-64 and over 15 and economic — price and income — variables have statistically significant long-run impacts on industrial electricity consumption.

The demographic variables have a larger impact than the economic variables on industrial electricity consumption.

The long-run elasticities of the consumption with respect to the population age groups are around unity. This means that a 1% growth in the population age groups cited above will cause an increase of around 1% in industrial electricity consumption. As section 2 explains, a growing population will demand more goods and services, including those produced by industry. To meet this increased demand, industry will increase its production of goods and services, requiring more inputs, including energy/electricity.

Keeping other factors constant, a 1% increase in the price of electricity for industry lowers consumption by 0.1% in the long run. Thus, price increases can lower electricity consumption, although the latter is remarkably unresponsive to the former in the Saudi Arabian economy.

Industrial electricity consumption is not very responsive to changes in income. In the long run, a 1% rise in industrial income increases industrial electricity consumption by between 0.2%-0.3%.

The estimated speed of adjustment coefficients indicate that the long-run relationships between industrial electricity consumption and economic and demographic variables remain stable over time.

Finally, we construct an error correction equation using the long-run estimation results. Instead of making projections using the equation, which is a partial equilibrium framework, we incorporate it into an energy sector augmented structural macroeconometric model. This is a general equilibrium framework, as the latter has certain advantages over the former (see Beenstock and Dalziel 1986). We make projections for industrial electricity demand through four scenarios alongside the reference case, i.e., business as usual up to 2025, using different assumptions for the population age group and energy price increases. The key takeaway from our projections is that future population growth will boost consumption, although consumption can be hampered by increased prices.

Since industry is, and will continue to be, one of the main drivers of economic growth in Saudi Arabia, policymakers might wish to carefully consider its electricity consumption, among other things. EPR can lower industrial electricity consumption, but not by a great degree. EPR would make industrial electricity consumption more efficient, generating extra revenues for the government that can be invested back into the economy. Policymakers, especially supply-side decision-makers, should be aware that Saudi Arabia's growing population will demand more goods and services and that in consequence, the industry will consume more electrical energy. Lastly, our findings show that the electricity consumption system can quickly absorb policymakers' interventions, such as EPR.

Introduction

Examining economic aspects of electricity consumption, mainly income and price elasticities, is of great importance for policymakers. These aspects can inform policymakers about two fundamental things: how the relationship between electricity consumption and its economic drivers evolved historically; and how given projections of these drivers will shape future consumption.

This information would prove useful to demand-side policymakers for managing electricity consumption using tools such as energy prices, tax rates and tariffs. It could also be useful for supply-side policymakers in planning the level of electricity supply required to meet future demand adequately (Burney 1995; Diabi 1998; Al-Sahlawi 1990, 1999; Atalla and Hunt 2016; Hasanov et al. 2016a). Lastly, this information would also be relevant for environmental protection purposes such as reducing emissions (Mundaca 2017; Khondaker et al. 2014; Alkhatlan and Javid 2015).

It is also important to assess the demographic aspects of electricity consumption for the same reasons. Therefore, a number of studies considered demographic variables, such as population, its age groups and urbanization in their analyses (Holte Dahl and Joutz 2004; Bianco et al. 2009, 2013; Anderson 1971, 1973; Halvorsen 1972; Sadorsky 2014; Poumanyvong and Kaneko 2010; Parikh and Shukla 1995; York 2007; Liddle and Lung 2010, 2014; Jones 1989, 1991; Al-Mulali et al. 2013; Hasanov et al. 2016b; Mohamed and Bodger 2005; Pielow et al. 2012). These studies considered either total electricity consumption or the breakdown of it into two large groups, residential and non-residential, as dependent variables. In this regard, the demographic aspects of industrial electricity consumption have been considerably overlooked. To the best of our knowledge, we are aware of only four studies

(Campbell 2018; Burke and Abayasekara 2017; Bilgili et al. 2012; and Mount et al. 1973) which include demographic variables along with economic variables in their analyses of industrial electricity consumption. Given the above, we believe that an analysis of the demographics of industrial electricity consumption would make a valuable contribution to this under-examined area of the literature.

Demographic variables can impact industrial energy consumption through demand for industrial goods and services, as was empirically found in Campbell (2018), Burke and Abayasekara (2017), Bilgili et al. (2012), and Mount et al. (1973). In addition, Campbell (2018) finds that demographic indicators can impact industrial electricity consumption independent of income and price. Further, Campbell (2008) shows that omitting demographic factors in the industrial electricity consumption analysis may cause upward bias in the income and price elasticities. Second, and more importantly, the magnitude of the impact of the demographic variables cannot be estimated or measured in the standard demand-side approach so as to see whether they are important for industrial energy consumption or not. This is because the standard demand equation contains only the explanatory variables of income and price, as Bhattacharyya and Timilsina (2009) discuss in their survey of existing energy demand models. For that reason, the studies noted above augmented their standard demand equations by including demographic variables. However, those studies do not provide theoretical ground for including the demographic variables in the standard energy demand framework.

Thus, the objective of our research is: (a) to develop a framework which will enable us to examine the impacts of demographic changes on industrial electricity consumption alongside economic indicators; (b) to apply the framework

to the historical data of Saudi Arabia; (c) to make projections up until 2025.¹

Unlike previous studies, our research modifies the standard approach by reconsidering the theory of energy demand and suggests a framework for measuring the explicit impacts of demographic changes on industrial electricity consumption. We believe that such a framework would be useful for studies that aim to empirically assess the impacts of demographic changes on industrial energy consumption alongside economic indicators in developed and developing economies. In addition, the framework could be applied not only to industrial electricity consumption but also to the industrial consumption of other energy products.

In the empirical analysis part of this study, we apply the suggested framework to the Saudi Arabian data. The demographic aspects of Saudi Arabia are worth considering. For example, the average per annum growth rate of the population was about 3% during 1984-2016. Moreover, the share of the population aged between 15-64, one of the most important demographic indicators for an economy and society, has increased from 54.1% in 1984 to 68.8% in 2016 (UN 2018). Considering that demographic indicators usually change slowly over time, these changes are substantial, with energy consumption implications that should not be ignored.

In addition to the aforementioned background, the present study is also important because of the following factors. Industry is the main contributor to Saudi Arabian economic growth. It is worth noting that the average share of industrial value added in gross domestic product (GDP) during the period 1984-2016 was about 60.6%.² Additionally, the realization programs of Saudi Vision 2030, such as the National Industrial Development and Logistics Program, National Transformation Program, Public

Investments Program, and the strategic roadmaps for Saudi Arabia's development, consider industry to be one of the main drivers of future economic growth (SV2030). Moreover, Vision 2030, especially the Fiscal Balance Program, highlights the importance of energy price reform (EPR), which aims to bring domestic energy prices up to international reference levels in order to make the economy and society more efficient and to increase government budget revenues (FBP 2018). EPR will have an impact on domestic energy consumption, given that, unlike in many other countries, domestic energy prices in Saudi Arabia, including industrial energy prices, have been administratively set very cheap and constant in nominal terms - even decreasing when the rate of inflation is taken into account - for a number of years (Atalla and Hunt 2016; Jun 2013; Al Iriani and Trabelsi 2015; Matar et al. 2017; Matar and Anwer 2017). However, the successful implementation of EPR will also depend on understanding the impact of prices on energy consumption in the entire economy, including industry. This requires an assessment of the impact of any change in prices on energy consumption. Such estimations will provide policymakers with a clearer idea of what can be expected from EPR in terms of lowering energy consumption and increasing government revenues.

In this paper, we employ a cointegration and error correction modeling methodology. For this purpose, we use auto regressive distributed lags (ARDL) bounds testing as our main approach, together with Johansen and fully modified ordinary least squares (FMOLS) methods. One of the advantages of ARDL is that it outperforms its counterparts in small samples. We find that both population groups, aged 15-64 and aged 15 and above, have statistically significant positive effects on industrial electricity consumption in the long run. We also found that income and price exert statistically significant positive and negative impacts, respectively, on consumption.

However, their impacts are smaller than those of the demographic variables. Moreover, the speed of adjustments from the short-run disequilibrium toward the long-run equilibrium is quite fast. In addition, different projections up until 2025 have shown that future increases in electricity consumption will mainly be driven by population growth.

Three main policy insights can be derived from this study. Policymakers should expect that EPR will reduce industrial electricity consumption, but not by a great extent because the price effect is very small. At the same time, they should consider that the growing population aged 15-64, as well as 15 and above, will lead to increased industrial electricity consumption. Finally, policy interventions in industrial electricity consumption could be fully absorbed by the established system in less than a year.

This study contributes to the existing literature, first, by developing a theoretical framework for assessing the effects on energy consumption of both demographic indicators and economic factors, rather than considering the demographic indicators atheoretically. Second, to the best of our knowledge, this is one of the first studies globally, and the first study focused on Saudi Arabia, that

estimates industrial electricity consumption as a function of both demographic and economic factors. Third, our simulations were based on a set of different electricity prices to provide insights as to how EPR could shape industrial electricity consumption between 2018 and 2025. This is an important and hotly debated question for Saudi Arabia due to the ongoing economic reforms in the Kingdom. Our simulations also reveal the role of the growing population in future electricity consumption. Fourth, our projections are not based on one single equation, which is a partial equilibrium framework, but result from employing an energy sector augmented macroeconometric model, the KAPSARC Global Energy Macroeconometric Model (KGEMM), a general equilibrium model. Clearly, models representing an entire economy using a set of behavioral equations and identities can provide richer and more adequate information for a given process, since they consider the economy as a complete system, rather than through a single equation or other partial equilibrium frameworks (see Beenstock and Dalziel [1986] among others). Finally, we implement a number of robustness checks, in terms of both specification and methodology, to provide policymakers with more accurate assessments on industrial electricity consumption in Saudi Arabia.

Theoretical Framework

This section describes the framework we develop. It allows us to consider a demographic indicator as a factor of energy demand alongside economic factors.

It is theoretically obvious that a standard energy demand equation, in which the price of energy and income are the explanatory variables, is a relationship derived from the production function under different assumptions (see Uri [1982]; Beenstock and Dalziel [1986] among others). However, as Bhattacharyya and Timilsina (2009), among others, state, the standard energy demand equation might not be a relevant framework in some circumstances, depending on the research question(s) investigated. For example, Beenstock et al. (1999) show that using capital stock provides more accurate estimates than using income in the energy demand equation, while Beenstock and Dalziel (1986) discuss how the standard framework might be an incomplete account of energy demand since the relationship between energy and GDP is also affected by other production factors, such as labor and capital. This is especially the case where substitution and complementary effects between energy and other production factors are considered (see Pindyck [1979]; Uri [1982] Hisnanick and Kyer [1995] among others for theoretical discussions and empirical estimations).

For the reasons mentioned above, some researchers have reconsidered the theory of the standard energy demand equation, and modified or augmented it to suit their purposes (e.g., see seminal papers by Nordhaus [1975]; Beenstock and Willcocks [1981]; Beenstock and Dalziel [1986]).

Theoretical reconsiderations: Energy demand function with a demographic variable

Industry produces output (Q) using the inputs of

labor (L), capital (K) and energy (E), which can be expressed as the undefined function of (1):

$$Q = F(L, K, E) \quad (1)$$

where F shows production process/technology that transforms inputs to output.

Equation (1) can be expressed through the Cobb-Douglas type production function (Cobb and Douglas, 1928), using Taylor expansion and ignoring the higher order terms (see Nordhaus [1975] among others):

$$Q = AL^\alpha K^\beta E^\gamma \quad (2)$$

where A is total factor productivity and α , β and γ are the elasticities of production, with respect to labor, capital and energy, respectively.

It can be assumed that (a) a cost function exists as a dual function of the production function; (b) factor pricing is based on average cost and fixed markup; (c) there is also a well-behaved preference function in the economy and, thus, the demand for goods and services is a function of price and income; (d) all the functions follow the Cobb-Douglas type of specification; and (e) first-order conditions are derived assuming cost minimization. Then, the following energy demand equation can be derived from equation (2) based on the above assumptions:

$$e = a_0 + a_1 p_L + a_2 p_K + a_3 p_E + a_4 y \quad (3)$$

a_0 includes constant term and error term and a_1 , a_2 , a_3 , a_4 are the elasticities to be estimated econometrically; p_L , p_K , p_E are the prices of labor, capital, and energy; y is the industrial income. In other words, p_L is wage and p_K is cost of capital. All the small letters are the natural logarithmic expressions of the corresponding variables.

The mathematical derivation of equation (3) is described in Hasanov and Mikayilov (2018) and can be obtained from the author on request. Note that a similar kind of theoretical framework for energy demand is derived by Nordhaus (1975) and Beenstock and Dalziel (1986) among others.

Note that equation (3) has been considered in the literature to investigate industrial energy/electricity consumption (see Beenstock and Willcocks [1981]; Hawkins [1977]; Shirani et al. [2015], among others).

The following equation (4) for labor demand, l_D , can be derived from equation (2) under the same assumptions as above:

$$l_D = b_0 + b_1 p_L + b_2 p_K + b_3 p_E + b_4 y \quad (4)$$

where all the variables are the same and $b_i, i=1, \dots, 4$ are the respective to be estimated.

Macroeconomic theory sets out that the supply of labor, l_S , is mainly driven by real wage, p_L and working age population, pop (Beenstock and Dalziel 1986; Bloom and Freeman 1986; Fair and Dominguez 1991; Bloom et al. 2003; Olsson 2013; ILO 2016).³

$$l_S = c_0 + c_1 p_L + c_2 pop \quad (5)$$

Assuming $l_S = l_D$ and then solving (4) and (5) for p_L will yield the following equation:⁴

$$p_L = d_0 + d_1 pop + d_2 p_K + d_3 p_E + d_4 y \quad (6)$$

where,

$$d_0 = \frac{c_0 - b_0}{b_1 - c_1}; d_1 = \frac{c_2}{b_1 - c_1}; d_2 = \frac{-b_2}{b_1 - c_1}; d_3 = \frac{-b_3}{b_1 - c_1}; d_4 = \frac{-b_4}{b_1 - c_1}.$$

Finally, in equation (3), if we replace p_L with its expression in equation (6) and perform some

re-expressions, the following relationship for energy demand can be obtained:

$$e = \varphi_0 + \varphi_1 pop + \varphi_2 p_K + \varphi_3 p_E + \varphi_4 y \quad (7)$$

where, $\varphi_0 = a_0 + a_1 d_0; \varphi_1 = a_1 d_1; \varphi_2 = a_2 + a_1 d_2;$

$$\varphi_3 = a_3 + a_1 d_3; \varphi_4 = a_4 + a_1 d_4.$$

For the notational purpose, we express equation (7) in the following econometrically estimable form:

$$eci = \varphi'_0 + \varphi'_1 pop + \varphi'_2 cc + \varphi'_3 epi + \varphi'_4 yi + \varepsilon \quad (8)$$

where we decompose φ_0 into intercept, φ'_0 and error term, ε ; eci is the industrial electricity consumption; pop is the working age population; cc is the cost of capital in the industry; epi is the price of electricity for industry; yi is the industrial income. It is expected that the working age population and industrial income should have positive impacts, while the cost of capital and price should have negative impacts on industrial electricity consumption, i.e., $\varphi_1 > 0$ and $\varphi_4 > 0$; $\varphi_2 < 0$ and $\varphi_3 < 0$.

The framework we derived here is similar to equation (8) in Beenstock and Dalziel (1986) but differs from it in three ways. First, unlike Beenstock and Dalziel, our aim here is to modify the existing energy demand framework to account for the effects of demographic changes. Second, our framework is derived assuming cost minimization, while Beenstock and Dalziel assume profit maximization. Third, we have income as an explanatory variable in our framework while Beenstock and Dalziel do not. We may also derive the same equation as (4) in Beenstock and Dalziel, in which income/output is present, assuming profit maximization instead of assuming cost minimization. However, in this case, we have to make the assumption that output is constant in the production function framework

when the first order conditions are derived. We think that this would be an irrelevant assumption because Beenstock and Dalziel argue that output should change when production inputs, or their prices, change. We believe that including income as one of the main explanatory variables in the energy demand equation enriches the information set for policy analysis and/or forecasting.

The impact of the working age population on industrial electricity consumption

From the demand-side viewpoint, it is quite straightforward to understand how industrial income and the electricity price can influence industrial electricity consumption in the above framework. Accordingly, we do not discuss them here. Instead, we consider how the working age population, POP can affect industrial electricity consumption, ECI.

Naturally, a growing population, including POP, will demand more goods and services, including industrial products. Conceptually, this demand can be met in three ways: increased demand for industrial products resulting from population growth is entirely met by imports; it is totally met by the domestic production; the demand is partially met by imports and partially by the domestic production. The first two options are extremes, and it is less likely countries would implement them due to several reasons. For example, no country should

wish to be totally dependent on the imports because of the security and sustainability of supply. Besides, relying on the imports curbs the development of the domestic industry, which would create extra jobs and revenues for a country. Also, relying on imports to meet the domestic demand is not favorable for the international trade balance as it creates pressure on the domestic currency, and if there are not enough revenues, then it will lead to trade deficit. The second option does not seem realistic either, as it would be difficult for a country to be internationally competitive on all the demanded industrial products. Thus, the third option appears more realistic for any country to implement because of the reason given above. In this channel, population increases will cause increased industrial electricity consumption through demand for the industrial products. Figure 1 illustrates this channel in a simple way.

The figure shows that when the demand for industrial products rises due to population growth, industry increases its output to meet demand.⁶ To do this, industry can pursue the following pathways in its production process:

(a.i) it increases output by increasing consumption of all the inputs, i.e., intermediate goods (I), including electricity (ECI), as well as capital (K) and labor (L) in the production process. This is the case when industry follows the production input growth path (Jorgenson et al. 2014; Saari 2006; Genesca and Grifell 1992).

Figure 1. Schematic illustration of the impact of POP on the ECI.⁵

Source: Author's own construction.

(a.ii) it increases output by increasing the consumption of I and ECI but keeps the amounts of K and L unchanged in the production process. This can happen in different ways. For example, industry can utilize its spare production capacity, since it is usually not running at full capacity. Or industry has made improvements in its capital and/or labor productivity.

(a.iii) it increases production by increasing the consumption of I, K and L but keeps ECI unchanged in the production process. This is the case when industry follows the production input growth path and its electricity intensity declines. A decline in electricity intensity may imply an increase in electricity efficiency.

(a.iv) it increases the production by not increasing consumption of the inputs - i.e., I, ECI, K and L are all kept unchanged. This is the case when the industry has a decline in electricity intensity and an increase in the productivity of K and L, as well as having total factor productivity (TFP) growth, such as technological progress, and advanced production technology.

If industry follows (a.i) or (a.ii) or both, then we should find that the impact of POP on ECI is economically meaningful and statistically significant in the econometric estimations. Another possible channel in (a.i) is that when POP grows L may increase, which might result in an increase in ECI as additional employees will result in greater industrial electricity consumption. In both channels, it is reasonable to think that POP has a stronger correlation with ECI than it does with the industrial value added (YI), which is desirable for econometric estimation purposes. Conceptually, this is the case because when POP increases, all production inputs, including electricity, will be increased to produce more output to meet the demand. Then, YI may increase as it is a derivative variable, determined as the output less the intermediate consumption according to the System of National Accounts (SNA 2008).

Conversely, if industry follows (a.iii) or (a.iv) or both, then we should not find any economically meaningful and statistically significant impact of POP on ECI and, additionally, we should observe a declining trend in electricity intensity.

Data and Preliminary Analysis

Data

We use annual time series data for Saudi Arabia spanning 1984-2016 for the following variables:⁷

Industrial electricity consumption (ECI). This is the total final industrial electricity consumption taken from the International Energy Agency (IEA 2018). It is expressed in tonnes of oil equivalent (toe) and converted into million tonnes of oil equivalent (Mtoe).

The price of electricity for industry (EPI). Nominal prices for industrial electricity consumption are taken from the KAPSARC data portal and measured in Saudi riyals per kilowatthour (SAR/kWh) (KAPSARC 2018). We then use the price deflator for the industrial value added to convert the nominal prices to real values. In order to isolate oil price volatility, oil mining and quarrying was excluded when the price deflator was constructed. The deflator is calculated as a percentage ratio between nominal and real industrial value added and 2010 is selected as a base year. Both nominal and real value added are taken from Saudi Arabia's General Authority of Statistics (GaStat 2018). We convert SAR/kWh to toe to be consistent with the consumption measure.

Industrial value added (YI). This is the value added in the industry in millions of Saudi riyal at 2010 prices. It is constructed as a sum of the value added in the industrial sectors such as manufacturing, mining and quarrying, following the International Standard Industrial Classification. We collected the required data from GaStat (2018).

Working age population. The population aged between 15 and 64 is considered the working age population. The population aged between 15 and 65 and above can also participate in the labor market, especially in developing economies (see ILO [2016];

OECD [2019] among others). Thus, both age groups can be considered in the framework developed here as well as in the empirical analysis. P1564 is the Saudi population aged 15-64, while P1565A is the Saudi population aged 15-65 and above. The data for both variables comes from the United Nations' World Population Prospects (U.N. 2018). These data are measured in thousand people and include all residents of Saudi Arabia, regardless of legal status or citizenship.

Cost of capital (CC). This is the real user cost of capital, measured as a percentage. Usually the variable is constructed as the sum of the interest cost of holding capital and the depreciation rate of capital, adjusted by the inflation rate. Because it is difficult to find the interest cost of holding capital in practice, it is usually proxied by the long-term interest rate in macroeconomic level studies (see Olsson 2013 among others). We could not find the long-term interest rate for Saudi Arabia. One-month, three-month, six-month and 12-month interest rates on Saudi riyal deposits are available from SAMA (2018) for the period 1997-2016. Another interest rate, the Saudi Arabia Interbank Offered Rate (SAIBOR), is available from Thomson Reuters; the longest-dated SAIBOR is one year. None of these variables can be considered long-term interest rates, because long-term interest rates usually have a duration of more than five years. Hence, as a proxy, we took the United States (U.S.) seven-year Treasury note yield, at constant maturity, adjusted for the inflation rate. We did this considering that Saudi Arabian monetary policy strictly follows U.S. monetary policy, as the exchange rate of the Saudi riyal has been pegged to the U.S. dollar (US\$), at the constant rate of 3.75 SAR/\$1, since 1986. Therefore, Saudi Arabia's interest rates follow U.S. interest rates very closely (see Algahtani [2015] among others). Note that Cappelen and Magnussen

Data and Preliminary Analysis

(1996) use a similar approach for the user cost of capital for Saudi Arabia.

Earlier studies of industrial electricity consumption (e.g., Al-Sahlawi [1999]) took total GDP as an income measure and the consumer price index (CPI) as a deflator for converting nominal electricity prices to real values. Unlike those studies, we use industry-specific value added and a price deflator following Bernstein and Madlener (2015). By being industry specific, we avoid the potential bias that might stem from aggregation (see Bohi [2013]; Stoker [1993]; Blundell and Stoker for aggregation bias and its consequences).

We illustrate the historical developments of the variables over the period 1984-2016 in Figure 2.

The ECI graph in Figure 2 illustrates that there are two different development paths in its time profile: in 1984-2006 and 2007-2016. ECI has increased with the average per annum growth rate of 5.2% in the first sub-period, while in the second sub-period its

average per annum growth rate accelerated to about 12%. This break could be caused by the number of industrial customers and/or the share of electricity in total industrial energy consumption. Both have increased significantly since 2007 as the graphs in Figure 3 illustrate.

The increase in the number of customers may be related to the substantial increases in government expenditure, including investment spending, and non-oil private investment since 2003 (SAMA 2018). It usually takes three to five years for capital formation to transform into operating assets. Figure 2 shows no similar break since 2007 in any of the explanatory variables considered here. Therefore, for the sake of obtaining proper results, we capture this break using a dummy variable in the unit root test and cointegration (long-run) analysis. The graph also shows that the growth rates of ECI have slowed considerably since 2014. We think that this is related to the decline in the price of oil and, consequently, the decline in economic activity, coupled with a significant increase in the industrial electricity price.

Figure 2. Time profile of the variables.

Source: Author's own construction.

Figure 3. Number of industrial customers and share of electricity in total industrial energy use. **Graph a:** Number of industrial subscribers of SEC.
Source: SAMA (2018). **Graph b:** The share of electricity in the industrial total energy use of, in percent.
Source: IEA (2018).

Generally, the nominal price of electricity for industry follows a stepwise pattern over the period 1984-2016. The tariff was 582 SAR/toe during 1984-1994, rising to 1,163 SAR/toe in 1995-1999. The nominal price was 1,334 SAR/toe and 1396 SAR/toe in 2000 and 2001, respectively. It was increased again, by 12.5%, in 2010 and by another 11.1% in 2011 and was then unchanged until 2016, when it was raised by 20% and was 2,093 SAR/toe.⁸ Real prices, i.e., EPI, demonstrated an uneven trajectory over the period, as Figure 2 illustrates. As the graphs show, a negative association between ECI and EPI should be expected, especially since 2001.

YI has increased over the period, but two distinct development paths can be observed, pre- and post-1992. While the average per annum growth rate was about 10% from 1984-1992, it declined to 2% in the post-1992 sub-period. This shift could be associated with institutional and structural changes in Saudi Arabia's upstream and downstream oil industry in the late 1980s and early 1990s (see Metz 1992 among others). The same shift also characterizes drilling and oil refining. Again, because the Kingdom's economy relies heavily on oil, any changes to the oil sector affect the rest of the economy.

Turning to demographic variables, it is notable that more than half of the Saudi Arabian population is aged between 15 and 64. P1564 has grown from 6.856 million in 1984 to 22.169 million in 2016, with an average annual growth rate of 3.7%. To put this another way, the percentage of people aged 15-64 in the Kingdom's population has increased from 54.1% in 1984 to 68.8% in 2016. Among other things, these facts have important implications for energy consumption and economic development, including in the industrial sector.

The cost of capital followed a downward trend over the period, as Figure 2 illustrates, in part because the inflation rate grew more rapidly than the nominal long-term interest rate.

Note that we use the natural logarithmic expression of the above variables in the empirical analysis, except for the cost of capital, which is notated in small letters. For example, *eci* is the natural logarithmic expression of ECI. For the capital cost, we use the level of variable since its values are quite small, and some of them are negative, as can be seen in Figure 2.

Preliminary analysis

The purpose of the preliminary analysis is to find out which of the option(s) discussed in sub-section 2.2, i.e., a.i-a.iv, would be the case for Saudi Arabia.

Figure 4 shows the industrial electricity intensity during the period considered.⁹

Electricity intensity grows over time: slowly until 2007 and very rapidly afterward. Also, the pattern shown in the graph of ECI in Figure 2 is very similar. This empirical evidence leads us to think that (a.iii) and (a.iv) are less likely cases for Saudi Arabian industry, in terms of keeping ECI unchanged in the production process. Moreover, it is hard to believe that Saudi Arabia, as a developing economy, has seen such an improvement in total factor productivity (TFP) that the economy can increase its level of industrial output without consuming additional amounts of the production inputs, including electricity. In fact, TFP in the economy has taken a steady downward trend, especially since 1992, and the industrial labor force has grown substantially over time, especially since 2008, as Figure 5 illustrates.

Figure 4. Electricity intensity in Saudi Arabia's industry.

Source: Author's own construction.

The above data analysis would indicate that Saudi Arabia's industry is more likely to follow case (a.i). Lastly, following the conceptual discussion described in endnote 9, we calculate the correlation coefficients between $p1564$, and eci , yi over the estimation period 1984-2016. We do the same for $p1565a$. We used the natural logarithmic expressions of the variables in the correlation analysis in order to be consistent with the econometric analysis. The coefficient between $p1564$ and eci is 95.4% while that between $p1564$ and yi is 91.1%. The coefficient between $p1565a$ and eci is 95.4% while that between $p1565a$ and yi is 91.3%. It appears that these findings support the discussion in endnote 9. It also indicates that we should not expect any multicollinearity issue in our estimations.

Thus, our conclusion from the preliminary analysis of the data is that a positive and statistically significant impact of POP on ECI can be expected in the econometric estimations of equation (8).

We will use the following two versions of (8) in the econometric analysis since we consider two age groups.

$$eci_t = \varphi'_0 + \varphi'_1 p1564_t + \varphi'_2 CC_t + \varphi'_3 epi_t + \varphi'_4 y_t + \varepsilon_t \quad (9)$$

$$eci_t = \varphi'_0 + \varphi'_5 p1565a_t + \varphi'_2 CC_t + \varphi'_3 epi_t + \varphi'_4 y_t + \varepsilon_t \quad (10)$$

where t means time indicating we conduct time series econometrics estimation and testing; ε and e are the error terms, respectively.

Figure 5. Saudi Arabia's TFP and industrial employment.

Graph a: TFP at constant national prices for Saudi Arabia, index 2011=1, annual, not seasonally adjusted.
Source: FRED (2018).

Graph b: Industrial employment, thousand persons.
Source: Author's calculation using GaStat (2018) data.

Econometric Findings

This section discusses the findings of the econometric analysis, i.e., unit root tests, the cointegration analysis and the robustness checks set out in Appendix C.

We started our empirical analysis with the unit root tests, as time series variables have stochastic properties such as non-stationarity, which should be taken into consideration. For a robustness check, we applied both conventional unit root tests and those accounting for structural breaks as described in Appendix B. Our overall finding from the tests results, documented in Table C1, was that the log levels of the variables were non-stationary, with and without structural breaks, depending on the variable considered. In particular, we found that the industrial electricity consumption, our dependent variable, follows an $I(1)$ process, with a structural break in 2007. We also found that the first differences of the log levels of all the variables were stationary. In other words, our variables followed an $I(1)$ process. The non-stationarity implies that any impact on the log levels of our variables can be permanent and, thus, their mean, variance and covariance will change over time. Hence, it is hard to predict future values for the variables if we use their log levels. This suggests that we should not use non-stationary forms, i.e., log levels, of the variables in predicting future values for them. Conversely, the stationary forms of our variables, i.e., the first differences in the log levels, assume that any impact on them is temporary. Therefore, the mean, variance and covariance of the stationary variables do not change over time. Note that socio-economic variables generally are not strongly stationary, but weakly stationary. It means that their mean, variance and covariance are not strictly constant over time. Strong stationarity holds true for the variables in the natural sciences. See detailed discussion in econometrics textbooks (e.g., Gujarati and Porter 2009). Stationarity is also known as the mean

reverting process, as the variables ‘dance’ around their mean over time. It would be more accurate to predict future values of the stationary variables since these values should return to their mean. For example, if a given value of the stationary variable at present is higher than its mean, then its future value can be expected to decline towards the mean (see Hara et al. [2009]; Hendry and Juselius [2000] among others).

We employed three cointegration methods, described in Appendix B, for robustness purposes. The test results documented in Tables C2-C6 indicated that the variables were cointegrated. Additionally, Table C4 showed that the number of the cointegrating relationship was not more than one. This means that the economic variables, income and price, and demographic variables - the population groups aged 15-64, as well as 15 and above - are cointegrated with industrial electricity consumption. Being cointegrated assumes that there is a common/shared trend between the non-stationary forms of the variables. In other words, they establish a long-run relationship by moving together, and any deviations from this relationship in the short run will be temporary and will adjust back to it. The economics of cointegration states that the relationship found between the variables is in line with economic theories or concepts. We found the long-run relationship between industrial electricity consumption, industrial income and the industrial electricity price were in line with demand-side economic thinking, which articulates that income and price have a positive and a negative impact, respectively, on consumption. As this is a core concept in economics, we do not think we need to explain why income has a positive effect on consumption or why price has a negative impact. The relationship between industrial electricity consumption and the demographic variables, i.e., the population groups aged 15-64, and 15-and-

above is in line with the theoretical framework developed earlier in this paper. We will detail these relationships later in this section.

The cointegration theory states that if there is a long-run relationship among variables, then the (log) level relationship between them is not spurious and can be used for policy analysis (see Engle and Granger [1987], among others). This allowed us to estimate numerical values of the long-run relationships between industrial electricity consumption and socio-economic variables. To draw robust conclusions for industrial electricity consumption, we estimated two different specification forms and used two different methods. The numerical findings for the relationships are documented in Tables C3, C5 and C6.

We found that both the population groups - aged 15-64 and 15-plus - have positive and statistically significant impacts on industrial electricity consumption in the long run. More specifically, for the population group aged 15-64, we found that the elasticity of industrial electricity consumption is 1.0 in the level specification. This means that, if all other factors are constant, a 1% increase in the age group of 15-64 causes a 1% increase in industrial electricity consumption in the long run. This numerical relationship varies from 1.4 to 1.7 when per capita specification form is considered.

The estimation results for the age group 15-above are very close to those that we found for those aged between 15 and 64. A 1% increase in those aged 15-above is associated with a 1% increase in industrial electricity consumption in the long run. For the per capita relationship, this elasticity is in the range of 1.5-1.8.

The positive effects of the age groups on industrial electricity consumption are consistent with the theoretical framework described earlier in this paper.

The demographic variables and the theoretical and conceptual channels through which they can positively impact industrial electricity consumption are the key things we consider in this research. We are unable to compare our estimated coefficients with those of other researchers as we are not aware of any other studies that have estimated the effects of the population age groups on industrial electricity consumption in Saudi Arabia. We are only aware of Diabi (1998), who estimated the impact of urbanization as a demographic variable on the total electricity consumption of the Saudi Arabian regions and found the coefficient ranged between 0.93 and 1.30. We think that our estimation results are not directly comparable with those of Diabi as the dependent variables and demographic indicators used are different in these two studies. Note, however, that our findings are in line with those of studies conducted for other countries (Mount et al. [1973], Burke and Abayasekara [2017] for the U.S.; Bilgili et al. [2012] for Turkey; and Campbell [2018] for Jamaica), which examined the impact of demographic indicators on industrial electricity demand and found a positive relationship.

Regarding the impacts of the economic variables, estimation results for the price effect are consistent across the estimations in terms of sign, size and significance, regardless of whether a level or per capita relationship is considered. This can be taken as a sign of robustness. The price has a negative and statistically significant impact on consumption. All other things being constant, a 1% rise in the industrial electricity price leads to a 0.1% decline in industrial electricity consumption in the long run. We do not need to explain the negative association between price and consumption in this paper, given that it is one of the cornerstones of economics. However, we have some empirical observations to share. First, the estimated magnitudes show that consumption is very insensitive to price changes.

Second, an earlier study conducted by Eltony and Mohammad (1993) of the Gulf Cooperation Council (GCC) countries' industrial electricity consumption found this elasticity as -0.20, and to be statistically significant. We have two explanations for the inelastic price effect found in these studies. First, the industrial electricity price was very cheap historically due to its heavy subsidy, as Eltony and Mohammad explain. Jun (2013) also highlights the fact that the industrial electricity price was the cheapest among all the energy sectors in Saudi Arabia. Second, the inelastic price effect may be related to the fact that industrial users are more sensitive to the prices of other energy products than to the electricity price as they have a greater share in total industrial energy consumption. For example, between 1984-2015 the shares of industrial use of natural gas and heavy fuel oil (HFO) in total energy use in the Kingdom's industry averaged 39.3% and 31.6% respectively, while electricity averaged only 7% of the mix. Consequently, increases in the prices of natural gas and HFO would likely have a much bigger impact on industrial energy consumption compared with electricity price rises. For example, Al-Faris (1997) finds long-run price elasticity of total fuel oil consumption being -0.7 for 1970-1991 while Bhattacharyya and Blake (2009) estimate it to be -1.4 from a dynamic specification, over the period 1982-2005 for Saudi Arabia.

We found that income has a statistically significant and positive impact on consumption. It is reasonable to assume that an increase in income level will lead to an expansion of industrial production, where energy is one of the inputs. The long-run elasticities of consumption with respect to income are very close to each other across different specifications and methods. This shows that our estimated coefficients are robust and could be used for policymaking purposes. The elasticity is 0.2 in the level specification, while it

is 0.3 in the per capita specification (Tables C3, C5 and C6). This means that a 1% increase in industrial value added results in a 0.2% or 0.3% increase in industrial electricity consumption. Note that our findings for income are in line with the findings of the earlier studies conducted for Saudi Arabian industrial electricity consumption. For example, both Al-Sahlawi (1999) and Eltony and Mohammad (1993) found that income elasticity of industrial electricity consumption was inelastic for Saudi Arabia. An inelastic income elasticity is also supported by the other industrial electricity demand studies conducted for other economies, such as Jamil and Ahmad (2010), Dilaver and Hunt (2011), Inglesi-Lotz and Blignaut (2011), and Arisoy and Ozturk (2014). Our explanation for the inelastic income effect is the subsidized industrial electricity price, as discussed. That low price makes it possible for industrial customers to purchase the required amount of electricity, even if their income level is low. Another possible explanation is that electricity is a necessity product for industrial customers, as it does not seem efficient for them to substitute it with other types of energy. For example, taking electricity from the distribution or transmission network is more cost-effective for industrial customers than generating it from burning fuel or natural gas. Shirani et al. (2015) find that in Iran, an oil-rich country with a small open economy, a set of circumstances similar to that of Saudi Arabia, long-run cross-elasticity of electricity with respect to natural gas in the industrial sector is very low (0.09), and it is impossible in the short run for the sector to change to the machinery required to make the switch from electricity to natural gas. Moreover, both the inelastic price and the income effects on industrial electricity consumption may be explained by the fact that the Saudi government has directly subsidized and invested in industry to boost the development of the industrial sector

and to achieve economic diversification and create jobs, as discussed in Eltony and Mohammad (1993).

Our estimated income elasticities for Saudi Arabia were lower than those obtained by Al-Sahlawi (1999) and Eltony and Mohammad (1993) who found elasticities of 0.66 and 0.89, respectively for Saudi Arabia. We explain this difference as follows:

(a) The estimation periods are different. The estimation period in Al-Sahlawi was 1975-1996 and in Eltony and Mohammad the period covered was 1975-1989, while our estimation period is 1984-2016.

(b) The income measures considered are different. It is not clearly reported which income measure was considered by Al-Sahlawi and our understanding is that the study divided nominal GDP by the consumer price index as an income measure, as shown in equation (1) in Al-Sahlawi (1999, 85). Eltony and Mohammad report that they took the contribution of the industrial sector to real GDP. For the sake of fairness, and without underestimating the efforts and contributions of the earlier studies, we think our approach is more accurate as it takes the industrial value added for industrial electricity consumption modeling in Saudi Arabia.

(c) Both the earlier studies used ordinary least squares (OLS) to estimate the relationship, using non-stationary variables without checking their integration and cointegration properties. As the cointegration theory articulated, and Al-Faris (2002) stated, the OLS results in such cases are spurious if a cointegrating relationship does not exist (Granger and Newbold 1974; Engle and Granger 1987; Kao 1999) and can be biased and inconsistent if a cointegrated relationship exists (Banerjee et al. 1986; Phillips and Hansen

1990; Phillips and Loretan 1991; Stock and Watson 1993).

(d) Al-Sahlawi only used income as an explanatory variable, while Eltony and Mohammad considered income and price but not demographic variables. Given the discussion by Campbell (2018) and others, it might be thought that the earlier studies could suffer from the omitted variable bias issue.

Finally, the estimated speed of adjustment (SoA) coefficients show that there is a stable long-run relationship among industrial electricity consumption and its demographic and economic determinants, and that any shock to this relationship is temporary. Although the variables may temporarily deviate from this relationship in the short run, they will adjust back to it in the long run. Another implication of the statistically significant and negative SoA coefficients found here is that long-run causality runs from the income, price, and population age groups to industrial electricity consumption. The magnitudes of the coefficients are very slightly smaller than negative unity. This indicates that after receiving shock(s), it takes slightly sooner than one year for industrial electricity consumption to completely adjust back to the long-run relationship.¹⁰ One possible explanation for this rapid adjustment is the nature of the established relationship between electricity consumption and its determinants that we found for Saudi Arabia's industrial sector. Consumption is irresponsive to changes in prices and income, mainly because of very low administered prices and the government's other supports for the industry. In that framework, market-related shocks to prices and their effects on consumption are quite limited; if the government increases the prices, it introduces a support mechanism at the same time. The government has been implementing

domestic energy price reforms, i.e., increasing prices, alongside fiscal and other reforms, but it has also been implementing industrial and household support packages since 2016 to mitigate the negative effects of the reforms (FBP 2018). Likewise, the government will increase its support for the sector if industrial income receives recessionary shocks, because the development

of the sector is one of the country's priorities, as discussed earlier. Thus, if consumption were responsive to changes in price and income, these changes would force consumption to deviate greatly from its long-run level, which would take a longer time to adjust to. In other words, industrial electricity consumption is capable of absorbing economic shocks thanks to government support.

Projections

This section makes projections of industrial electricity demand until 2025. First, we briefly introduce the estimated error correction model (ECM) specification and KGEMM, an energy sector augmented structural macroeconometric model that we will run to make the projections. We describe the underlying assumptions for the projections and, finally, we discuss the results of the industrial electricity consumption projections, paying particular attention to the effects of a growing population and reformed domestic energy prices.

Estimated ECM

As was discussed for the unit root findings, stationary conditions of the variables should be used for forecasting purposes. For this, an ECM specification in which all the variables are stationary should be estimated. Two types of ECM specifications, i.e., level and per capita, can be developed and estimated since we have meaningful long-run relationships for both. Here we estimated the ECM specification based on the ARDL long-run estimations results for equation (9'), as this equation links industrial electricity consumption to price, income and the population age group of 15-64 explicitly. Details of the ECM are given in Appendix D.

We then incorporated the estimated ECM into KGEMM to make projections of industrial electricity consumption in the general equilibrium framework. This is more relevant than a partial equilibrium framework - e.g., a single equation - as Beenstock and Dalziel (1986), among others, have shown.

Brief overview of KGEMM

KGEMM is a policy tool designed to examine the effects of internally-made decisions by domestic policymakers as well as interactions between the global economy and the Saudi Arabian energy-

macroeconomic environment (KGEMM 2018). KGEMM is a general equilibrium, energy sector augmented, structural macroeconometric model. It represents mainly the demand side of the economy with some elements from the supply side. It has eight blocks interacting with each other to represent Saudi Arabia's macroeconomic and energy relations, as shown in Figure 6.

In a broader sense, KGEMM can provide two kinds of insight:

(a) The effects of the global economy, such as the oil price, foreign direct investment, world demand, and import price index, on Saudi Arabia's energy-macroeconomic environment. Developing a feedback loop for the model from Saudi Arabia to the rest of the world through the impact of mainly crude and refined oil exports on the world demand and prices is under progress.

(b) The interrelationship within and between different sectors of Saudi Arabia's economy.

The model has about 700 annual time series variables, divided into endogenous and exogenous variables. The exogenous variables are mainly global economy-related variables and representations of domestic policies. The endogenous variables are determined within the model, using either behavioral equations or identities. The behavioral equations are ECMs, and they express behavioral relationships between the variables, including domestic and global ones, in the long run and in the short run. The identities are mainly based on the System of National Accounts. As an econometric methodology, KGEMM employs times series cointegration and error correction modeling. Appendix E gives details of the blocks and other characteristics of KGEMM.

Figure 6. Schematic illustration of KGEMM.

Source: KGEMM (2018).

Underlying assumptions of the projections

Our main purpose in the scenario analysis is to see how domestic energy price reform and an increasing population aged 15-64 will shape the future consumption of electricity in Saudi Arabia's industrial sector. In line with this, and to facilitate a full understanding, we designed two different assumptions for each of the variables alongside the reference case, business as usual (BaU). Table 1 outlines the assumptions.

Our projections cover the period 2017-2025. As Table 1 shows, we have two cases in addition to the reference case. Case 1 reflects a high price increase and a low population increase, while Case 2 presents a relatively low price increase and a high population increase.

In the BaU, i.e., reference case we assumed that until 2025 the price of electricity for industry would remain the same as in 2016.¹¹ The population aged between 15 and 64 will grow in line with the U.N.'s 'medium variant' projection for the population growth in Saudi Arabia (U.N. 2018). This variant assumes

Projections

Table 1. Underlying assumptions for the projections.

Stage	Year	Change in the industrial electricity price	Rise in the population aged 15-64
Reference case	BaU	Fixed at the level of 2016 up to 2025, i.e., 2,093.4 SAR/toe.	It will grow in line with the U.N.'s 'medium variant' population growth projection for Saudi Arabia.
Case 1	S1	It will gradually rise and reach twice the 2016 level, i.e., 4,186.8 SAR/toe in 2025.	As in BaU
	S2	As in BaU	It will grow in line with the U.N.'s 'low variant' population growth projection for Saudi Arabia.
Case 2	S3	It will gradually rise and reach international level, i.e., 3,052.9 SAR/toe in 2025.	As in BaU
	S4	As in BaU	It will grow in line with the U.N.'s 'high variant' population growth projection for Saudi Arabia.

Notes: BaU=Business as Usual; S1=Scenario 1; S2=Scenario 2; S3=Scenario 3; S4=Scenario 4.

Source: Author's own calculation.

that the population will increase by, on average, 1.6% per annum and reach 25.6 million in 2025.

To see the separate effects of the electricity price and the population on future electricity consumption, we have two scenarios for each case. This is to ensure that the effects are not mixed, and so that we can differentiate between the impacts of the price and population changes, respectively. Scenario 1 increases the electricity price by 100% and maintains population growth as it is in the BaU scenario. This is in order to see how a price increase of that magnitude would lower future electricity consumption compared with BaU, under which the price is fixed. Scenario 2 looks at how much electricity consumption will decrease in the future compared with the BaU scenario if the increase in the population aged 15-64 follows the U.N.'s 'lower version.' Under this scenario, the population would grow by, on average, 1.4% per annum and reach 25.1 million in 2025, while the price remains the same as it is in BaU. Scenario

3 will explore the extent to which electricity consumption will fall compared with BaU because of the moderate price increases to reach international benchmarks (46% compared with 2016), with population growth following the BaU scenario. Finally, Scenario 4 sets the population growth higher than BaU, i.e., an average 1.9% increase per annum over the period, following the U.N.'s 'high version,' while keeping the price fixed as it is under the BaU scenario. This should increase future consumption compared with the BaU case.

The price assumptions made in Table 1 are in line with Saudi Vision 2030 (SV2030), in particular, the Fiscal Balance Program (FBP 2018). This strategic roadmap outlines significant increases in domestic energy prices, including electricity prices, for the coming years and states that domestic prices should be at about the level of international prices. The purpose is to make the Saudi economy and society more efficient and to raise additional revenues for the government budget. Details of

the programs can be found in the references cited. For the international price in Scenario 3, we took the average price of electricity for industry in the U.S. for the 10 years from 2008 to 2017, which was about \$0.07/kWh or 3,052.9 SAR/toe. We took that as the target price for Saudi Arabia to reach in 2025. Our assumptions as to the population aged 15-64 are based on U.N. population projections for Saudi Arabia. Specifically, we applied the growth rates of the total population increases in all three variants to the age group over the projection period. Note that the values of the industrial price deflator for the projection period were taken from the Oxford Economics Global Economic Model database and the same values were used for all the five scenarios to deflate the nominal prices (Oxford Economics 2018). We used the same value set for all scenarios to see the pure impact of the electricity price changes, which is the main purpose of the projection exercise. If we were to take a different value set for the price deflator in different scenarios, the impact on future industrial electricity consumption would be a mix of electricity price changes and price deflator changes. Lastly, we treated the industrial value added, our income measure, as endogenous, to be determined from the model, rather than treating it as exogenous. Earlier studies (e.g., Al-Sahlawi 1999) took income measure as exogenous in projecting the future values of industrial electricity consumption. This is usual for single equation and partial equilibrium model frameworks and is one of their disadvantages (see discussion in Beenstock and Dalziel [1986]). If there is a full equilibrium model, then GDP, or other income measures including industrial value added, should not be treated as exogenous variables, because they are not exogenous by nature, unlike population, administrated prices, taxes, and tariffs, for example. They are endogenous, meaning they depend on different policy measures, internal and external changes, among other things.

Consequently, choosing to determine the income measure endogenously from the model is a more accurate representation of reality. This is one of the merits of our projections.

Results of the projections

Figure 7 shows that ECI increases from 4.3 Mtoe in 2016 to 6.2 Mtoe in 2025 in BaU (blue line), while it reaches 6.1 Mtoe and 5.9 Mtoe in S2 (red line) and S1 (green line) in 2025. Average per annum growth rates for ECI in the three scenarios are 4.3%, 4.1%, and 3.6%, respectively.

At a first reading, it may appear from Figure 7 that the price increase reduces ECI significantly compared with the effect produced by population changes. However, a closer look reveals the opposite: ECI is very insensitive to price increases and sensitive to population growth. The price in S1 is on average 55.6% higher than that in BaU, and ECI decreases, on average, by 3.3% in S1, compared with BaU over the projection period. It appears that a 1% increase in price lowers ECI by only 0.1%. On the population side, the percentage difference between S2 and BaU is, on average, -1% and that causes the same magnitude of change in ECI. That is to say, a 1% decrease in the population lowers ECI by 1%.

Figure 8 demonstrates projections for BaU, S3 and S4. According to the graph, ECI increases from 4.3 Mtoe in 2016 to 6.2 Mtoe, 6.02 Mtoe and 6.35 Mtoe in BaU (blue line), S3 (dark grey line) and S4 (yellow line) in 2025. Average annual growth rates for ECI in the three scenarios are 4.3%, 3.9%, and 4.5%, respectively. The results shown in Figure 8 also support the evidence that we observed for the projections earlier. It is clear from Figure 8 that ECI is quite sensitive to population growth: on average a 1.14% increase in the population in S4 compared

Projections

Figure 7. Industrial electricity consumption (ECI) projections for BaU, S1, and S2.

Source: Author's own construction.

with BaU leads to an average 1.12% increase in ECI in S4 against BaU. That is to say, a 1% increase in population in S4 relative to BaU causes ECI to rise by 1%. The price increases on average by 25.5% in S3 compared with BaU. This results in an average 1.7% decrease in ECI as a percentage difference between S3 and BaU. A 1% rise in the price is thus associated with a 0.1% decrease in ECI.

The key findings from our projections are as follows:

Industrial electricity consumption has a one-to-one relationship with the population group aged 15-64.

Industrial electricity consumption is not very sensitive to price change. To lower consumption by 1%, the price has to be increased by 10%.

These two findings show that the numerical impacts of price and population age group on the consumption estimated in the empirical analysis section remain almost the same in the projections, although the income is treated endogenously.

There is no significant difference between ECI values in BaU and those in the scenarios. This can be explained by the previous two findings. In other words, even though the price

Figure 8. Industrial electricity consumption (ECI) projections for BaU, S3, and S4.

Source: Author's own construction.

is increased drastically (100% in S1 and 46% in S3), its impact on ECI is very small. On the other hand, population rises have a large effect on ECI, but population growth across the scenarios is very small. The maximum growth is 1.1% in S4.

We tried to find ECI projections for Saudi Arabia from other sources and studies so as to compare them with ours. We only found total electricity consumption projections up to 2018 from Index Mundi via the Central Intelligence Agency (CIA) World Factbook for Saudi Arabia (Index Mundi 2019). The projected values are 272 billion kWh and 292.8 billion kWh in 2017 and 2018,

respectively. Note that ECI was slightly higher than 17% of total Saudi electricity consumption between 2013 and 2016 (IEA 2018). It is reasonable to assume that this share will remain more or less the same up to 2018 because the structure of the industry - including technology, capital stock and energy efficiency - cannot change significantly in two years. We then calculated industrial electricity consumption for 2017 and 2018 from the above source and they were 4.0 Mtoe and 4.3 Mtoe, respectively. Our projected values for ECI in BaU for 2017 and 2018 are 4.31 Mtoe and 4.34 Mtoe, respectively. The projections from the different sources appear similar to one another.

Conclusion and Policy Insights

A number of studies have explored the demographic aspects of residential or total electricity consumption. However, we are aware of only four studies that considered this for industrial electricity consumption and unfortunately they did not provide a theoretical foundation for the demographic variables they employed. This motivated us to develop a framework in which industrial energy consumption is linked to demographic and economic factors. We then applied this framework to Saudi Arabia's industrial electricity consumption. There are a very limited number of studies analyzing Saudi Arabia's industrial electricity consumption, although the topic has drawn a lot of attention in developed and developing economies and industry is, and will continue to be, the main driver of Saudi Arabia's economic development. Moreover, the demographic aspects have been overlooked.

In order to produce more robust results, we employed different unit root and cointegration tests as well as long-run estimation methods. We also used two different specifications for estimating the long-run elasticities of industrial electricity consumption.

Finally, we made projections for Saudi industrial electricity demand up to 2025, using different assumptions for the population age group and energy price increases in the general equilibrium model framework.

Our main conclusions from the study can be summarized as follows:

Both the demographic and economic variables have statistically significant impacts on industrial electricity consumption in the long run. The long-run relationships of consumption are stable, and the full adjustment process from any short-run disequilibrium takes around a year.

Demographic variables have a larger impact on industrial electricity consumption than economic variables. The long-run elasticities of consumption with respect to the population age groups are around unity.

Industrial electricity consumption has an inelastic relationship with the economic variables. The long-run elasticities of consumption with respect to electricity price and income are about -0.1 and 0.2 (0.3), respectively.

The main takeaway from the projections made up to 2025 is that future industrial electricity consumption will be more responsive to population growth than to price increases.

It is a given that industry is, and will continue to be, one of the main drivers of Saudi Arabia's economic growth. Hence, electricity consumption, together with other related factors, should be taken into account in the decision-making process. In particular, policymakers should consider that although EPR would dampen industrial electricity consumption, it would not be by very much. They could also consider EPR as a means of increasing industrial efficiency. Another implication is that an increased electricity price would not hurt industry significantly, but could provide additional revenues for the state budget, which could then be circulated back to the economy as current or investment spending. Policymakers might also consider that consumption is quite responsive to population growth, meaning that a rising population should boost industrial electricity consumption. Finally, it should be noted that our research indicates that any policy changes/interventions will be absorbed by the system in about a year's time.

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Appendix A. Literature Review

A.1. Related literature on industrial electricity consumption

We are aware of only four studies for other countries and no study for Saudi Arabia that estimate the industrial electricity consumption effects of the economic and demographic variables together. These studies also investigate electricity consumption in other sectors. However, we only focus on the industrial sector for the purposes of our research. Mount et al. (1973) investigates the impact of population, alongside other variables including income and price, on industrial electricity consumption in the United States (U.S.) They use annual data for 47 states over the period 1947-1970 and estimate both time series and panel models. They employ OLS and instrumental variable methods for constant and time-varying specifications. The study found that population has a statistically significant positive impact on the industrial electricity consumption of different states, as well as a mean level of all states, with the elasticity of unity regardless of the method employed. This study shows that researchers considered the importance of the demographic variables for industrial electricity consumption as far back as the early 1970s. Hence, the study deserves appreciation although it does not address integration, cointegration or cross-section dependency and other issues of the panel data. We think this is understandable as the econometric methods for tackling these issues either had not been developed or were not widely employed in the early 1970s.

Another study, Burke and Abayasekara (2017), also estimates the industrial electricity demand effects of price, income, and population in the U.S. in the panel of 48 states between 2003 and 2015.

They find long-run population elasticity to be 0.86 and statistically significant regardless of whether instrumental or non-instrumental estimations' results are considered.

Bilgili et al. (2012) examines industrial electricity consumption in Turkey using linear, non-linear and artificial neural network models. The researchers carry out modeling over the period 1990-2007 and forecasting for 2008-2015. The study concludes that population is one of the important variables in modeling and forecasting industrial electricity consumption. However, it does not report the coefficient of population or consider the integration and cointegration properties of the data in the linear regression model.

Campbell (2018) investigates the impact of urbanization on industrial electricity consumption alongside price and income for Jamaica over the period 1970-2014. The study discusses how demographic indicators such as the urbanization rate can affect industrial electricity consumption, independent of price and income. The results from the autoregressive distributed lags (ARDL) estimations support this discussion as it finds that the urbanization rate has a statistically significant positive impact on industrial electricity consumption, both in the long run and in the short run. One of the key findings of this study is that it empirically shows that omitting demographic variables - such as population or the urbanization rate - causes an upward bias in the estimated coefficients of industrial electricity demand with respect to other explanatory variables, i.e., price and income. We acknowledge that this is one of very few studies that considers the effects of demographic changes on industrial electricity consumption. We address the following two points. First, we provide a theoretical ground for including the urbanization rate in the standard demand-side equation. Second, we

discuss why the urbanization rate has a very large impact on industrial electricity consumption (the study estimated that a 1% rise in the urbanization rate results in a 17% increase in industrial electricity consumption in the long run).

Note that there are many studies devoted only to the economic aspects of industrial electricity consumption in different countries. We do not review them in this section since they are not of direct interest to our research and they are comprehensively surveyed in papers such as Bhattacharyya and Timilsina (2009), Wang and Mogi (2017), Hosoe and Akiyama (2009), Fan and Hyndman (2011), Bilgili et al. (2012), and Suganthi and Samuel (2012).

A.2. Literature survey on Saudi electricity consumption

Most studies of electricity use in Saudi Arabia have focused on either total or residential electricity consumption. They have also focused mainly on economic factors - income and price - while ignoring demographic factors. Given this, here we review the studies devoted not only to industrial electricity consumption but also to residential and to total Saudi electricity consumption, using time series as well as cross-sectional and panel data. We hope that such a broad review will be useful for those interested in studying Saudi Arabia's electricity consumption.

Table A1 below documents the studies. We have the following observations:

1. Only three studies investigated Saudi Arabia's industrial electricity consumption, although the topic is important in the electricity modeling literature (see early seminal studies on industrial electricity consumption by Baxter and Rees [1968] and Ang [1988], as well as industrial electricity consumption

studies for different countries, such as Jobert and Karanfil [2007], Jamil and Ahmad [2010], Dilaver and Hunt [2011], Arisoy and Ozturk [2014], Adeyemi and Hunt [2014], Bernstein and Madlener [2015], Adom [2017]). Al-Sahlawi (1999) presents a time series study, while the other two, Eltony and Mohammad (1993) and Liddle and Lund (2014), present panel studies and do not report Saudi-specific estimation results. In addition, the first study considered only income and the third study considered only urbanization as a regressor, while the second included price and income but no demographic variables in the analyses. Accordingly, one might think that Al-Sahlawi and Liddle and Lund could suffer from the omitted variable bias issue, given that income or urbanization are not the only factors affecting electricity consumption (see theoretical discussions in Lutkepohl [1982] and Triacca [1998]; and empirical discussions in Odhiambo [2009] Hasanov et al. [2017]). Moreover, neither Al-Sahlawi (1999) nor Eltony and Mohammad (1993) addressed the non-stationary properties of the data used and, thus, the results might be misleading, as Al-Faris (2002) argues, among others. Regardless of the imperfections, we value these three studies because they are the only ones published to date that shed some light on Saudi Arabia's industrial electricity consumption.

2. Six out of 20 studies consider demographic variables in their analysis, and only one of them, Atalla and Hunt (2016), is a time series study.

3. Only six of the 20 studies in the table are time series research, our literature survey found. In addition, three out of the six might potentially suffer from imperfect estimations, as they do not account for the non-stationarity properties of the data used in their analysis. Studies by Matar and Anwer (2017) and Matar (2017) conduct simulations and do not estimate electricity consumption elasticities with respect to the determinants. Moreover, the most recent study, Atalla and Hunt (2016) covers only the period to 2012. In other words, the last five or

six years of Saudi electricity consumption have not yet been explored in the literature, although it is a period that includes an oil price collapse and the consequent slowdown in Saudi Arabia's economic activity, as well as the Kingdom's reforms of domestic energy prices, fiscal policy and institutional issues.

4. Many studies are panel and cross-sectional, in which Saudi Arabia is one of many countries covered, not the main focus. Additionally, electricity

consumption is not the research objective of six out of the nine panel studies; rather they use it as a regressor to conduct the Granger causality test.

To conclude: there is a need for time series studies of industrial electricity consumption which consider both demographic and economic factors. In this regard, we believe that our research fills a gap in the existing literature of industrial electricity consumption.

Table A1. A review of the studies on Saudi Arabia's electricity consumption.

Name	Electricity variable used	Period	Countries	Data type	Method	LR income elasticity	LR price elasticity	Demo-graphic indicator used	Remarks
Al-Sahlawi (1990)	TEC and Peak EC	1970-1985	SA	T	OLS	1.21*	-	None	Price variable and its coefficients were not reported.
Eltony and Mohammad (1993)	REC, Commercial EC, Industrial EC	1975-1989	GCC including SA	P	OLS	0.89	-0.20	None	The coefficients are for the GCC.
Burney (1995)	TEC per capita	1990	93 countries including SA	C	RC	0.621	-	Level of literacy; urbanization ² (0.013)	The coefficients are for Saudi Arabia.
Diabi (1998)	TEC for the Saudi Arabian regions	1980-1992	SA	P	OLS, CHTA, CCTA, FE, RE, MLE	0.09 to 0.49	-0.14 to 0.01	Urbanization ¹ (0.93 to 1.30)	CR, WR, ER, SR, and NR were taken as the panel members.
Al-Sahlawi (1999)	Industrial EC, Residential EC, Average EC	1975-1996	SA	T	OLS	0.66	-	None	Price variable was not used.
Al-Faris (2002)	TEC	1970-1997	GCC including SA	T	VECM	1.65	-1.24	None	The coefficients are for Saudi Arabia.
Squally (2007)	TEC per capita	1980-2003	OPEC including SA	T	ARDL	-	-	None	Only GDP was used, but its coefficient was not reported.
Narayan, and Smyth (2009)	TEC per capita	1974-2002	ME including SA	P	FMOLS	-3.07	-	None	The coefficient is for Saudi Arabia.
Jun (2013)	No quantitative analysis was conducted. However, the following useful points have been discussed over the period 1962-2007: electricity generation, sectoral, including industrial, consumption for electricity and prices; energy efficiency; tariff systems and subsidies; government policy.								
Liddle and Lund (2014)	TEC, Industrial EC and REC	1971-2009	105 countries including SA	P	ECM	-	-	Urbanization ²	Only Granger causality between urbanization and EC variables was conducted.

Appendix A. Literature Review

Name	Electricity variable used	Period	Countries	Data type	Method	LR income elasticity	LR price elasticity	Demo-graphic indicator used	Remarks
Mohammadi and Amin (2015)	TEC per capita	1971–2011	79 countries including SA	P	ECM	-	-	Urbanization ²	For the group of countries where Saudi Arabia was included, it was found that GDP per capita and urbanization Granger cause the TEC per capita.
Karanfil and Li (2015)	TEC per capita	1980–2010	160 countries including SA	P	VECM, VAR	-	-	Urbanization ²	For the non-OECD group of countries where Saudi Arabia was included, it was found that GDP per capita and urbanization Granger cause the TEC per capita in the long run.
Salahuddin et al. (2015)	TEC per capita	1980–2012	GCC including SA	P	VECM	-	-	-	For the entire panel, it was found that GDP per capita Granger causes the TEC per capita.
Atalla and Hunt (2016)	REC	1985–2012	GCC including SA	T	STSM	0.48	-0.16	Population (0.80)	The coefficients are for Saudi Arabia.
Alabbas and Nyan-gon (2016)	Monthly TEC and REC and Regional EC	1992–2010	SA	T	OLS	-	-	None	The weather-based forecast model for Saudi Arabia.
Alrashed and Asif (2014)	REC	2012	SA	C	-	-	-	-	This was a survey analysis based on REC in the Eastern province. No estimations were conducted.
Matar (2017)	REC	2011	SA	C	OPE	-	-	None	OPE model-based simulations using changes in electricity prices for 2011.
Anto-nakakis et al. (2017)	TEC per capita	1971–2011	106 countries including SA	P	VAR	-	-	None	For the high-income countries where Saudi Arabia was included, it was found that GDP per capita Granger causes the TEC per capita.
Hasanov et al. (2017)	REC	1997–2014	OEC including SA	P	ECM	-	-	None	For the entire panel, it was found that employment has a short-run Granger causality on the REC.
Matar and Anwer (2017)	REC	2015	SA	C	OPE	-	-	None	OPE model-based simulations using changes in electricity prices for 2015.

Abbreviations: TEC=total electricity consumption; REC=residential electricity consumption; EC= electricity consumption; T=time series; P=panel; C=cross-sectional; SA= Saudi Arabia; GCC=Gulf Cooperation Council; ME=Middle East; OEC=Oil Exporting Countries; OPEC=Organization of the Petroleum Exporting Countries; OLS=ordinary least squares; CR=central region; WR=western region; ER=eastern region; SR=southern region; NR=northern region; ARDL=autoregressive distributed lags bounds testing; CHTA=the cross-sectionally heteroskedastic and timewise autoregressive; CCTA=cross-sectionally correlated and timewise autoregressive; MLE= the maximum likelihood estimator; RC= random coefficient; FMOLS=fully modified OLS; OPE=optimization based partial equilibrium model; * Calculated by the author using provided parameters in a given study; 1 and 2 urbanization variables are defined as the number of telephones in operation in a given region and share of people living in urban area, respectively.

Source: Author's own construction.

Appendix B. Econometric Methodology

B.1. Unit root tests

Economic, energy and demographic variables are not usually stationary over time. Hence, testing the integration properties of variables is important before estimating the relationship between them. A number of empirical studies mention that there is no need to check the integration order of the variables if the ARDL method is applied. However, two main points should not be ignored: (a) at the very least, the integration order of the dependent variable should be checked, because if it is an $I(0)$ variable, then performing cointegration tests and estimating long-run relationships becomes meaningless; (b) if the ARDL analysis involves an $I(2)$ variable, its results might be misleading. Hence, we employ two conventional unit root tests, i.e., the augmented Dickey-Fuller (ADF) (Dickey and Fuller 1981) and the Phillips-Perron (PP) (Phillips and Perron 1988) for robustness purposes. As a further robustness check, we also use unit root tests with structural breaks, because our consumption and income data potentially have structural breaks in their development paths, as discussed in the data section above. We use the ADF test with structural breaks (ADFBP) developed by Perron (1989), Perron and Vogelsang (1992a, 1992b), and Vogelsang and Perron (1998) for this purpose. Note that the advantage of the ADFBP is that it can be used regardless of whether a break (i) occurred suddenly or smoothly; (ii) is in trend or level or in both; (iii) the date is known or unknown. Gujarati and Porter (2009), Enders (2015), Stock and Watson (1993), and Dolado et al. (1990) provide details of the ADF and PP tests, while Perron (2006), Zivot and Andrews (1992), and Banerjee et al. (1992) discuss the unit root tests with structural breaks.

B.2. Cointegration methods

We analyze the effects of the economic and

demographic variables on industrial electricity consumption using the cointegration and error correction modeling framework. The key advantage of the framework is that it can reveal three kinds of useful information for policymaking: the long-run relationship and short-run dynamics between the variables, as well as the speed of convergence from the short-run dynamics to the long-run equilibrium level (see Enders [2015], among others). We employ ARDL bounds testing as the main method to test cointegration and estimate the long-run relationship among our variables. The main reason for using the ARDL method is that it outperforms its counterparts and produces more consistent results in small samples, which is the case in our research. This method is quite well known and widely used, and as such we do not describe it here. Interested readers may consider Pesaran and Shin (1999) and Pesaran et al. (2001). To achieve more robust results for the cointegration properties of our variables, we also employ the Johansen method, and the Engle-Granger method based on fully modified ordinary least squares (FMOLS) estimations, alongside the ARDL bounds testing. It is widely known that the Engle-Granger method (Engle and Granger 1987) has some drawbacks compared with the Johansen and ARDL bounds testing methods (see Enders [2015] among others). Nonetheless, we use this cointegration method here for two reasons: as a robustness check, and because it has been employed in many other electricity/energy demand studies. The key reason for selecting the Johansen method from other cointegration methods is as follows: As discussed in Enders (2015) and Johansen (1988), if k number of variables are involved in the cointegration analysis, then there can be potentially a maximum $k-1$ number of cointegrating relationships among them. Enders and Johansen further state that only the Johansen cointegration test can reveal if there are more cointegrating relationships than one. The

implication of this discussion for us is that there can be more than one cointegrating relationship among our variables, because the number of variables considered in the equations above is more than two. The ARDL bounds testing method assumes only one cointegrating relationship among given variables, by default. If the number of cointegrating relationships is more than one, then they should be accounted for in order to rule out any potential issues. A description of the Johansen method can be found in Juselius (2006), Johansen (1988), Johansen and Juselius (1990, 1992) and Enders (2015).

As previously mentioned, for further robustness we also employ FMOLS in testing cointegration and estimating the level relationship among the variables. We do not use dynamic OLS (DOLS), a dynamic estimator, which may outperform FMOLS, a static estimator, but could also lead to over-parametrization, as Utkulu (2012) discusses. The reason for choosing FMOLS is that we already have a dynamic estimator, ARDL, which outperforms DOLS. Thus, we use FMOLS alongside ARDL to see how similar or different the estimation results from the static and dynamic methods are. Hasanov et al. (2016a) carried out the same kind of comparison. Readers interested in FMOLS may consider Phillips and Hansen (1990) and Phillips and Loretan (1991).

B.2.1. Small sample bias corrections in testing cointegration

To ensure our inferences about the cointegration properties of the variables are robust, we use a small sample bias correction in the ARDL bounds testing and the Johansen methods. Sometimes the Johansen method - the trace and maximum eigenvalue statistics - may indicate more than one cointegrating relationship between variables. However, the number of cointegrating relationships reduces to one, or none, after applying a small sample bias correction method. This is especially true when the sample size is small and the system (number of variables involved) is large, as discussed in Reinsel and Ahn (1992), Reimers (1992), and Cheung and Lai (1993). This is also the case for the ARDL bounds testing: it can suggest one cointegrating relationship before the small sample correction and none after applying it. Without describing and discussing the correction methods, note that in the ARDL bounds testing framework we use Narayan (2005) critical values alongside Pesaran et al. (2001) critical values, while in the Johansen framework we apply the adjustment to the sample values of the trace and maximum eigenvalue statistics suggested by Reinsel and Ahn (1992) and Reimers (1992).

Appendix C. The Results of the Econometric Analysis

This section presents, first, the results of the unit root tests and the main analysis, then it documents the results of the robustness checks.

C.1. Unit root test results

Table C1 reports the results of the ADF and PP unit root tests.

According to the ADF and PP test results, *eci* and CC are trend stationary variables. However, the graphical illustration of the variables in Figure 2 would not suggest a trend stationary process and it is clear from the graphs that *eci* has a break in its development trend from 2007 and that CC also has a break in its time path. It is more than likely that these breaks caused the ADF and PP tests to produce the results which contrast with the graphical illustration. It is well known in cases of

structural breaks that conventional unit root tests such as the ADF and PP are powerless and may yield misleading results (see discussions in Perron [1989] and Hansen [2001] among others). Since *eci* is our main variable of interest, we examine its stochastic properties in detail below. To this end, we employ the unit root tests with structural breaks developed by Perron (1989), Perron and Vogelsang (1992a, 1992b), and Vogelsang and Perron (1998) as a robustness check.

We include trend and intercept, allow a break in the trend and specify three lags as a maximum in the test equation. Moreover, we select the Schwarz information criterion to indicate the optimal lag. Finally, we specify 2007 as an additive break point. The tests produce the sample statistic of -2.49, while the critical values are -3.59, -3.87 and -4.47 at the 10%, 5% and 1% significance levels, respectively. In other words, the null hypothesis of *eci*, which

Table C1. The results of the unit root tests.

Variable	ADF test					PP test			
	Test value	C	t	None	k	Test value	C	t	None
<i>eci</i>	-4.90***	x	x		3	-4.11***	x	x	
<i>epi</i>	-1.54	x			0	-1.63	x		
<i>yi</i>	-3.23*	x	x		2	-2.18	x	x	
<i>p1564</i>	-1.58	x	x		2	-2.60	x	x	
<i>p1565a</i>	-1.54	x	x		2	-2.63	x	x	
<i>CC</i>	-3.87**	x	x		0	-3.87**	x	x	
Δeci									
Δepi	-5.07***			x	0	-5.06***			x
Δyi	-4.96***	x			1	-7.61***	x		
$\Delta p1564$	-3.04**	x			1	-2.88*	x		
$\Delta p1565a$	-3.12**	x			1	-3.03**	x		
ΔCC									

Notes: ADF and PP denote the Augmented Dickey-Fuller and Phillips-Perron tests, respectively. Maximum lag order is set to three and optimal lag order (k) is selected based on the Schwarz criterion; ***, ** and * indicate rejection of the null hypotheses of having unit root at the 1%, 5% and 10% significance levels, respectively; the critical values for the tests are taken from MacKinnon (1996). Estimation period: 1984-2016. None means that neither intercept nor trend is included in the test equation. Note that the final unit root test equation can include one of these three: intercept (C), intercept and trend (t) or none of them (None). x indicates that the corresponding option is selected in the final unit root test equation.

Source: Author's own construction.

has a unit root with the structural break in 2007, cannot be rejected, meaning that the variable is non-stationary. Juselius (2006), Hendry and Juselius (2001), among others, discuss that if there is a break in the trend of a variable, then there should be a shift in the first difference of it. This implies that Δeci has a level shift starting in 2007 and we should again use a unit root test with a breakpoint, rather than a conventional one. Accordingly, we include an intercept in the test equation, allow a break in it, and specify two lags as a maximum, with Schwarz as an information criterion. Lastly, we considered 2007 as the starting year of the new regime. The sample test statistic is now -5.63, greater than all the critical values at the 10%, 5% and 1% significance levels, respectively. This suggests that Δeci is a stationary process, with a level shift. Thus, we conclude that eci is non-stationary at its level and that the first difference of it is stationary, i.e., the variable follows an $I(1)$ process.

We apply the unit root tests with structural breaks to CC data with the same setup as discussed above. We find the sample statistic of -4.81 while the critical values are -5.72, -5.18 and -4.89 at the 10%, 5% and 1% significance levels. For the ΔCC , the test produces the sample statistic of -9.16, while the critical values are -4.95, -4.44 and -4.19. It can be concluded that CC is an $I(1)$ process.

With regard to the integration order of other variables, it can be concluded that they also follow $I(1)$ processes, based on the results of the ADF and PP tests in the table. In precise terms, the ADF test results strongly indicate that the null hypothesis of the unit root cannot be rejected for the level of the variables, although it can be rejected for the first difference of them. For y_i alone, the null hypothesis can be rejected at the 10% significance level in favor of trend stationarity. However, the PP test result for y_i indicates that it is a unit root process.

Moreover, the graphical illustration in Figure 1 does not demonstrate a deterministic trend pattern, as the time profile of the variable contains ‘ups’ and ‘downs’ attributed to the stochastic trend. A clear break in the time profile of y_i since 1992 can be observed, as discussed in the data section. To achieve robust inferences, we applied the unit root test with the structural break to y_i . The test yields the sample value of -3.41. This value is smaller than the critical values, which clearly indicates that the variable follows a unit root process with the structural break. We do not report detailed results from the test here but they are available on request.

Thus, we conclude that all the variables are non-stationary at their levels and the first difference forms of them are stationary.

C.2. Results of the main analysis

Our conclusion as to the integration order of the variables allows us to conduct the ARDL estimations.

We set the maximum lag order at two, and select the Schwarz information criterion to specify the optimal lag length, following the seminal studies by Pesaran and Shin (1999) and Pesaran et al. (2001). As demonstrated in Figure 1 and in the unit root test results, eci has a break in its trend in 2007. Therefore, we include a dummy variable in the estimates to capture this effect. The dummy variable is zero until 2007 and $t-2007$ in 2007 and thereafter, where $t \geq 2007$. See Perron (1989) for a detailed discussion of structural breaks and constructing dummy variables to capture them. For simplicity, we did not report the dummy variable in the estimated equations. We initially chose the maximum lag length as three, as in the unit root test (URT) section, but none of the variables picked

Table C2. ARDL estimation and test results.

Equation	(9)		(10)	
Selected specification	ARDL(2,0,2,0,0)		ARDL(2,0,2,0,0)	
Test results of the residual diagnostics, mis-specification and cointegration				
F _{SC} (2)	3.12	0.07	3.11	0.07
F _{ARCH} (2)	2.30	0.12	2.27	0.12
F _{HETR}	0.42	0.91	0.44	0.90
JB _N	1.23	0.54	1.25	0.54
F _{FF}	1.73	0.20	1.77	0.20
F _W	15.51 ^{A*}		15.52 ^{A*}	
Estimated long-run elasticities and SoA				
Regressor	Coef.	Prob.	Coef.	Prob.
<i>epi</i>	-0.09	0.08	-0.09	0.08
<i>yi</i>	0.21	0.04	0.20	0.05
CC	-0.004	0.72	-0.004	0.71
p1564	0.94	0.00	–	–
p1565a	–	–	0.96	0.00
<i>a</i>	-1.15	0.00	-1.16	0.00

Notes: *epi* is the dependent variable in the estimations; F_{SC} , F_{ARCH} , F_{HETR} , F_{FF} and F_W denote F statistics to test the null hypotheses of no serial correlation, no autoregressive conditioned heteroscedasticity, no heteroscedasticity in the residuals and no functional form misspecification and no cointegration in the Wald test, respectively; JB_N indicates the Jarque-Bera statistic to test the null hypotheses of normal distribution of the residuals. *a* denotes SoA coefficient; A indicates that sample statistic is greater than upper bound of the critical value of Pesaran et al. (2001) at the 1% significance level in the given combination of the regressors and intercept is included in the long-run equation. * indicates that a sample statistic is greater than the upper bound of the critical value of Narayan (2005) at the 1% significance level in the given combination of the regressors, number of observations and intercept is included in the long-run equation. Coef. and Prob. indicate coefficient and its probability. For simplicity, the deterministic regressors are not reported. Estimation period: 1984-2016.

Source: Author's own construction.

up the third lag. Because of this and given that we have five variables against 33 observations, we decided to set two lags as a maximum in order to avoid over-parameterization. To ensure that our estimation results are statistically reasonable and can be used for analysis and projection purposes, we check all the estimated specifications against the residual diagnostics tests, i.e., serial correlation, autoregressive conditioned heteroscedasticity (ARCH) and heteroscedasticity normality tests. We also check them against the functional

misspecification test, then we perform the bounds test for cointegration. If the test results indicate that there is a cointegration relationship between the variables, then we estimate long-run and speed of adjustment coefficients (SoA).

Both the estimated specifications successfully pass all the post-estimation tests of residual diagnostics and misspecification as Table C3 shows. Additionally, they establish a cointegration between the variables in the equations as the

Appendix C. The Results of Econometric Analysis

sample values of 15.51 and 15.52 are far greater than the bounds critical values from both Pesaran et al. (2001) and Narayan (2005). Moreover, the estimated coefficients of the explanatory variables are statistically significant, and they have expected signs in the selected specification. The only problem is that CC appears statistically insignificant in the estimations, although its negative sign is theoretically expected. Hence, we decide to exclude the variable from the analysis as it is not our main variable of interest. We also

tried using Saudi Arabia's three-month interbank rate, adjusted for inflation, to represent the cost of capital. However, it is not a relevant interest rate measure for this purpose. It appears insignificant and even deteriorates the other variables' sign and significance in (9) and (10). The results can be obtained from the authors on request. To this end, we estimate (9) and (10) without CC, and we call them (9') and (10'). The results are documented in Table C3.

Table C3. ARDL estimation and test results.

Equation	(9)		(10)	
Selected specification	ARDL(2,0,2,0)		ARDL(2,0,2,0)	
Test results of the residual diagnostics, mis-specification and cointegration				
F _{SC} (2)	3.31	0.06	3.29	0.06
F _{ARCH} (2)	2.02	0.15	1.99	0.16
F _{HETR}	0.49	0.85	0.51	0.84
JB _N	1.11	0.57	1.13	0.57
F _{FF}	1.73	0.20	1.78	0.20
F _W	19.44 ^{A*}		19.44 ^{A*}	
Estimated long-run elasticities and SoA				
Regressor	Coef.	Prob.	Coef.	Prob.
<i>epi</i>	-0.09	0.07	-0.09	0.06
<i>yi</i>	0.21	0.04	0.20	0.05
CC	0.96	0.00	–	–
p1564	–	–	0.98	0.00
p1565a	–	–	0.96	0.00
<i>α</i>	-1.15	0.00	-1.16	0.00

Notes: *eci* is the dependent variable in the estimations; F_{SC} , F_{ARCH} , F_{HETR} , F_{FF} and F_W denote F statistics to test the null hypotheses of no serial correlation, no autoregressive conditioned heteroscedasticity, no heteroscedasticity in the residuals and no functional form misspecification and no cointegration in the Wald test, respectively; JB_N indicates the Jarque-Bera statistic to test the null hypotheses of normal distribution of the residuals. α denotes SoA coefficient; A indicates that sample statistic is greater than upper bound of the critical value of Pesaran et al. (2001) at the 1% significance level in the given combination of the regressors and Intercept is included in the long-run equation. * indicates that sample statistic is greater than the upper bound of the critical value of Narayan (2005) at the 1% significance level in the given combination of the regressors, number of observations and Intercept is included in the long-run equation. Coef. and Prob. indicate coefficient and its probability. For simplicity, the deterministic regressors are not reported. Estimation period: 1984-2016.

Source: Author's own construction.

Now we have statistically acceptable and economically meaningful estimation results, as set out in Table C3. It should be noted that the significance and magnitude of the coefficients in Tables C2 and C3 are very close. Also, the estimated SoA coefficients are negative and statistically significant, as theoretically predicted in both tables.

In conclusion, the important points from the main analysis are as follows:

Both economic (*epi* and *yi*) and demographic (p1564 and p1565a) variables have statistically significant long-run impacts on *eci*. They also establish cointegrating relationships with *eci*.

The coefficient on *epi* is negative and the magnitude of it is about -0.1.

The coefficient on *yi* is positive, with the magnitude of about 0.2.

The magnitudes of the coefficients on the demographic variables are around unity.

The estimated SoA coefficients indicate that the cointegrating relationships are stable over time. This means that any deviation from these relationships is temporary and returns to equilibrium.

C.3. Results of robustness checks

To ensure the relationships and numerical values that we find between *eci* and the explanatory variables in the previous section adequately represent reality, we conduct three kinds of robustness checks.

The first addresses the concern that there might be more than one cointegrating relationship between the variables. The ARDL bounds testing method cannot identify this, as discussed in the methodology section. Hence, we apply the Johansen cointegration test to equations (9') and (10'). Following the methodology described in Juselius (2006), among others, we first estimate VARs for equations (9') and (10') and set the lag order at two, as we do in the ARDL estimations. We find that a two lag order is optimal for equation (9'), while it was three for equation (10'). The optimal lags selections are based on having non-serially correlated residuals, as well as information criteria. We include the break dummy variable in the VARs as an exogenous variable, again as we do in the ARDL estimations. More information and test results are available on request. The test results are summarized in Table C4.

Table C4. Johansen cointegration test results.

Equation	(9')		(10')	
Null hypothesis	$r = 0$	$r \leq 1$	$r = 0$	$r \leq 1$
λ^a_{trace}	49.61**	21.81	44.08	20.71
λ^a_{max}	27.80**	14.62	23.38	16.09

Notes: The cointegration test type considered here assumes there is intercept in VAR and cointegration equation; r is the rank of Π matrix, i.e., number of cointegrated equations; λ^a_{trace} and λ^a_{max} are the small sample adjusted version of the trace and max-eigenvalue statistics; ** denotes rejection of the null hypothesis of no cointegration at the 5% significance level; Critical values for the cointegration test are taken from MacKinnon et al. (1999). Estimation period: 1984-2016.

Source: Author's own construction.

Appendix C. The Results of Econometric Analysis

Table C4 shows that there is only one cointegrating relationship for (9') and no cointegrating relationship for (10'), according to the small sample bias adjusted trace and max-eigenvalue statistics. The key finding is that none of the statistics indicate more than one cointegrating relationship either for (9') or (10'). Failing to reject the null hypothesis of no cointegration is a well-known weakness of the Johansen method when the sample size is small, as discussed in Johansen (2002). Moreover, having no relationship does not seem relevant, given that the literature usually finds one cointegrating relationship among energy consumption, its price and income.

ARDL and its bounds testing outperforms other cointegration methods in small sample sizes, as Pesaran and Shin (1999) and Pesaran et al. (2001) show. Recall that the ARDL bounds testing results in Tables C2 or C3 indicate that there is one cointegrating relationship between the variables in (9') and (10') after the small sample bias correction, i.e., using Narayan (2005) critical values.

Thus, our conclusion from this robustness check is that we can rely on the ARDL bounds testing results and consider that there is one cointegrating relationship between the variables in (9') and (10').

Table C5. ARDL estimation and test results using per capita forms.

Equation	(9'')		(10'')	
Selected specification	ARDL(2,0,2,0)		ARDL(2,0,2,0)	
Test results of the residual diagnostics, mis-specification and cointegration				
$\chi^2_{SC} (2)$	3.30	0.06	3.27	0.06
$\chi^2_{ARCH} (2)$	2.31	0.12	2.28	0.12
$\chi^2_{HETR} (15)$	0.55	0.81	0.57	0.79
JB_N	1.04	0.60	1.05	0.59
F_{FF}	0.79	0.38	0.85	0.37
F_W	14.28A		14.23A	
Estimated long-run elasticities and SoA				
Regressor	Coef.	Prob.	Coef.	Prob.
<i>epi</i>	-0.09	0.10	-0.09	0.09
<i>yi_pc</i>	0.26	0.02	0.25	0.03
p1564_sh	1.38	0.00	–	–
p1565a_sh	–	–	1.45	0.08
p1565a	–	–	0.96	0.00
<i>a</i>	-1.11	0.00	-1.11	0.00

Notes: *eci_pc* is the dependent variable in the estimations; *_pc* and *_sh* attached to the variables' mnemonics indicate that a given variable is in per capita terms; F_{SC} , F_{ARCH} , F_{HETR} , F_{FF} and F_w denote F statistics to test the null hypotheses of no serial correlation, no autoregressive conditioned heteroscedasticity, no heteroscedasticity in the residuals and no functional form misspecification and no cointegration in the Wald test, respectively; JB_N indicates the Jarque-Bera statistic to test the null hypotheses of normal distribution of the residuals. α denotes SoA coefficient; A indicates that sample statistic is greater than upper bound of the critical value of Pesaran et al. (2001) at the 1% significance level in the given combination of the regressors and intercept is included in the long-run equation. * indicates that sample statistic is greater than upper bound of the critical value of Narayan (2005) at the 1% significance level in the given combination of the regressors, number of observations and Intercept is included in the long-run equation. Coef. and Prob. mean coefficient and its probability. For simplicity, the deterministic regressors are not reported. Estimation period: 1984-2016.

Source: Author's own construction.

The second robustness check deals with the specification forms. We used the natural logarithm level of the variables in the estimations above. Sometimes studies conduct analyses using a per capita form of variables instead of (log) level form. Following this, we expressed equations (9') and (10') in per capita form and denote them (9'') and (10''), respectively. In other words, we rescaled the variables on both sides of the equations by total population, except for the price variable, i.e., *epi*. Total population data is from the U.N. (2018). We applied the same chains of estimation and testing procedures to (9'') and (10'') as we did in sub-section C.2. to see whether we could still obtain economically meaningful and statistically significant relationships. Table C5 documents the estimation and test results.

In order to save space, we do not discuss the results here, except to mention that the estimation results

are meaningful economically and statistically, as shown in Table C5. The main conclusion from the second robustness check is that the estimation results in per capita form support those obtained using the level form.

The third robustness check revisits the first two robustness checks but uses another cointegration test and long-run estimators, namely FMOLS.¹² Table C6 presents the estimation and test results.

Note that the test and estimation results in Table C6 strongly support those shown in Tables C3-C5.

Our overall conclusion from the robustness checks is that the results obtained from the main analysis in sub-section C.2. are robust and can be used for analysis and projection purposes.

Table C6. FMOLS estimation and test results.

Equation	(9'')		(10'')		(9'')			(10'')	
Cointegration test results									
EG _T ^a	-7.19 ^A		-7.22 ^A		-7.06 ^A			-7.08 ^A	
EG _z ^a	-34.31 ^A		-34.49 ^A		-33.53 ^A			-33.71 ^A	
Estimated long-run elasticities									
Regressor	Coef.	Prob.	Coef.	Prob.	Regressor	Coef.	Prob.	Coef.	Prob.
<i>epi</i>	-0.10	0.06	-0.10	0.05	<i>epi</i>	-0.08	0.10	-0.08	0.11
<i>yi</i>	0.20	0.04	0.18	0.06	<i>yi_pc</i>	0.29	0.01	0.27	0.01
p1564	1.05	0.00	–	–	p1564_sh	1.69	0.00	–	–
p1565a	–	–	1.08	0.00	p1565a_sh	–	–	1.77	0.00

Notes: *epi* and *eci_pc* are the dependent variables in the estimations, respectively; *_pc* and *_sh* attached to the variables' mnemonics indicate that a given variable is in per capita terms; EG_T^a and EG_Z^a are the degree of freedom adjusted Engle-Granger tau- and z-statistics; A indicates that sample statistic is greater than the critical value of MacKinnon (1996) at the 1% significance level; Coef. and Prob. mean coefficient and its probability. For simplicity, the deterministic regressors are not reported. Estimation period: 1984-2016.

Source: Author's own construction.

Appendix D: ECM Estimation and Testing Results

We first construct an error correction term (ECT) using the estimated long-run coefficients for equation (9') in Table C3 and one lagged level values of the variables. It can be expressed as follows:

$$ECT = eci_{t-1} - (-0.09 \cdot epi_{t-1} + 0.21 \cdot yi_{t-1} + 0.96 \cdot p1564_{t-1} + 0.09 \cdot DTB2007_{t-1} - 11.21)$$

Then, general unrestricted ECM is specified, containing ECT, two lags of the dependent and explanatory variables, as well as contemporaneous values of the explanatory variables and the dummy variable ($\Delta DTB2007$). Finally, applying the GTSMS, we arrive at a final ECM (see Campos et al., 2005). The coefficients and post-estimation test results of the final ECM are presented in Table D1.

Note that ECT has a negative SoA coefficient, as theoretically expected, and is statistically significant. The magnitude of it is very close to that in Table C3 for equation (9'), although they were estimated using different approaches. This indicates that the estimation results are consistent and are

reasonable to use for analysis and projections purposes. Additionally, the coefficients of the other explanatory variables have theoretically expected signs and they all are statistically significant, except for the one on the price change. We keep the price in the specification for two reasons: First, economically, we believe that the price change is a part of the data generation process for the changes in industrial electricity consumption. Second, statistically, excluding it causes some instability in the final specification, as the recursive estimate tests indicate, and also a decline in R-squared and adjusted R-squared. Note that this kind of research decision, i.e., to have an insignificant price in the final ECM specifications, has also been made in other energy demand studies (e.g., see Hartley et al. [2008]; Joutz and Gardner [1996], among others). Finally, Panel B in the table indicates that the final ECM successfully passes the post-estimation tests of the serial correlation, ARCH, heteroscedasticity, normality as well as functional misspecification. The final ECM also successfully passes the specification stability tests. To save space, the tests results are not reported here but are available on request.

Table D1. Final ECM specification.

Panel A: Estimated coefficients of the final ECM specification

Regressor	ECT	Δeci_{t-2}	Δepi_t	Δepi_t	$\Delta p1564_t$	$\Delta DTB2007_t$
Coefficient	-0.98	-0.20	-0.07	0.35	1.22	0.14
Standard error	0.15	0.08	0.09	0.16	0.45	0.03
p-value	0.00	0.01	0.40	0.03	0.01	0.00

Panel B: Residuals diagnostics and mis-specification tests results

Statistic		F_{SC}	F_{ARCH}	F_{HETR}	JB_N	F_{FF}
Sample value		0.37	0.80	0.16	1.43	1.39
p-value		0.70	0.19	0.99	0.48	0.25

Notes: Δeci_t is the dependent variable; Δ denotes the first difference operator; F_{SC} , F_{ARCH} , F_{HETR} and F_{FF} denote F statistics to test the null hypotheses of no serial correlation, no autoregressive conditioned heteroscedasticity, no heteroscedasticity in the residuals and no functional form misspecification, respectively; JB_N indicates the Jarque-Bera statistic to test the null hypotheses of normal distribution of the residuals. Estimation period: 1984-2016.

Source: Author's own construction.

Appendix E: KAPSARC Global Energy Macroeconometric Model (KGEMM)

KGEMM – A Macroeconometric Model for Saudi Arabia

KAPSARC Global Energy Macroeconometric Model (KGEMM)

- **Objective**

A policy analysis tool examining the impacts of internally made decisions and global economic and energy shocks on the Saudi Arabian macroeconomic-energy environment.

- **How can KGEMM be utilized?**

Scenario analyses and projections for macroeconomic and energy indicators to support research and decision-making (e.g., SV2030 initiatives and targets).

KGEMM Structure

The model has eight blocks interacting with each other to represent Saudi Arabia's macroeconomy and energy linkages.

KGEMM Structure

Energy module

This module contains demand for energy in the economy.

Energy is represented by

- electricity,
- natural gas,
- crude oil,
- refined fuel types (such as HFO, diesel, gasoline, kerosene etc.).

For the following sectors

- residential,
- industrial,
- government and commercial services,
- agriculture sectors.

External module

It will mainly cover international trade and investment.

- Exports of goods and services broken into oil and non-oil goods.
- Imports of goods and services
- Foreign Direct Investments inflow

KGEMM Structure

Price module

CPI. Aggregate and 12 sub-components in line with KSA consumption basket
Price Deflator. Aggregate and 14 sub-components in line with KSA economic activity
Price of Energy (electricity, natural gas and refined fuel products)

Fiscal module

Government current spending
Government capital spending
Government oil revenues
Government non-oil revenues. Also, includes:
- Revenues from existing non-oil activities, domestic energy sales, Umrah and Hajj visa fees, other visa fees
- New initiatives in Fiscal Balance Program, such as Expat levies, Value Added Tax, Luxury goods tax, Idle land tax and others.

Monetary module

Monetary aggregates (M0, M1, M2 and M3)
Time, Demand, and Foreign currency deposits
Interest rates
Exchange rates

KGEMM Structure

Real module

Gross Domestic Product
Value added in the Oil sector,
Value added in the Non-oil sector
14 sectorial value added in line with KSA economic activity breakdown
Intermediate, Final and Total Demand by 14 economic activities
Private investment
Private income and consumption

Wages and Employment module

Total wages in the KSA economy
Employment by economic activity classification in KSA.

Population and age cohorts.

Total Population
Population broken down into 12 age groups
Population by gender
Population by Saudi and Non-Saudi

KGEMM characteristics

- ☐ Macro-econometrics combined with Input-Output framework
- ☐ Cutting-edge econometric methods.
- ☐ Flexibility and simultaneity in evaluating multiple research/policy questions.
- ☐ Easy to customize for different research/policy questions.

KGEMM main features

- ☐ Well-established theoretical foundation coupled with stylized facts of Saudi Arabia's economy.
 - Oil, non-oil, no conventional taxes, foreign labor, Islamic features, etc.
- ☐ Oil sector is not purely exogenous (interlinks between oil and non-oil sectors).
- ☐ Aggregate demand is disaggregated into the 12 economic activities (IO framework).
- ☐ Aggregate supply is sum of the 12 economic activities (PF framework).
- ☐ Detailed energy block: 14 energy demand relationships.

KGEMM Database

- 580+ annual time series variables as of July 01, 2019
- Representing Real, Energy, Fiscal & Monetary, External Sector, Labor Market, Prices and Wage blocks of the model.

Econometric methodology → GtSM approach+ Autometrics

Pooling all theoretical determinants and choosing final specification based on a range of econometric tests for diagnostic, stability and misspecification

An example: the GtSM approach for modeling the consumer price index (Lags are omitted for simplicity).

A general unrestricted model for CPI:

$$CPI = a_0 + \underbrace{a_1 GDP + a_2 M2 + a_3 IR}_{\text{Money market approach}} + \underbrace{a_4 FP + a_5 ER}_{\text{PPP approach}} + \underbrace{a_6 ULC + a_7 GAP}_{\text{Markup approach}} + e_t$$

Tests for
- Diagnostics
- Stability
- Misspecification

Final specification for CPI:

$$CPI = b_0 + b_1 * M2 + b_2 * FP + b_3 * GAP + \varepsilon_t$$

Autometrics selects the best specification automatically and thus saves time.

Theoretical underpinning and econometric methodology

Theoretical underpinning

A demand-side view of the economy with supply-side representations

Econometric methodology

General to specific modeling approach + Autometrics

Econometric methodology → ECM and encompassing test

ECM - Combination of long-run relationship, short-run dynamics and speed of adjustment

$$\Delta y_t = c + \underbrace{\alpha(y_{t-1} + bx_{t-1})}_{\text{Long-run relationship}} + \underbrace{\sum_{i=1}^n \varpi_i \Delta y_{t-i} + \sum_{i=0}^n \varphi_i \Delta x_{t-i}}_{\text{Short-run dynamics}} + u_t$$

Speed of adjustment

Encompassing test compares the explanatory power of alternative specifications to produce the best model.

What kind of questions can KGEMM address?

- ☐ Conducting macroeconomic-energy scenario analyses and projections.
- ☐ Evaluating the economic effects of domestic energy market changes (price and quantity).
- ☐ Simulating the effects of fiscal and monetary policy changes on the economy.
- ☐ Examining the interrelations between the oil and non-oil sectors of Saudi Arabia's economy.
- ☐ Providing short-run and long-run elasticities and speed of adjustment parameters.
- ☐ Illustrating the impact of the global economy (energy market, FDI, prices, etc.) on Saudi Arabia.
- ☐ Assessing the dynamic impacts of the labor market (wage and employment) on the economy.
- ☐ The above listed impact analyses can be done at macro and sectorial levels.

Endnotes

¹ We focus on electricity as a type of energy in this research. We will investigate the industrial consumption of other kinds of energy, such as crude oil, heavy fuel oil, diesel, and natural gas in forthcoming research.

² GDP and the industrial value added both include oil and non-oil related activities and are measured in million (2010) Saudi riyal.

³ Although the main factors of labor supply are wage and population age group, one can also consider other possible determinants of labor supply, such as tax rate, insurance, and preferences. However, we do not do so here because (a) our purpose is to link energy demand to demographic factors and (b) to keep our framework simple.

⁴ Standard macroeconomic frameworks usually assume labor supply equals demand for it, with the consideration of unemployment (and natural unemployment in the case of steady-state equilibrium). The framework developed here is valid regardless of whether actual unemployment or natural unemployment is considered.

⁵ For explanatory purposes we consider electricity separately, as it is our main discussion point here, although it is usually included in intermediate goods and services.

⁶ Conceptually, the industry may increase output not for the purpose of meeting domestic demand but so as to export more, i.e., to meet global demand. As discussed above, this case is also less likely because countries try to meet their domestic demand first. In reality, economies have a mixture of both options.

⁷ Our empirical analysis starts in 1984 as the industrial electricity price on the KAPSARC data portal starts that year. Additionally, time profiles of the other variables considered in this research prior to 1984 are quite volatile, which could reduce the accuracy of the estimations.

⁸ In other words, 0.18 SAR/kWh.

⁹ We took the ratio of the electricity consumption (ECI) to the industrial value added (YI) and then converted the resulting series to the index series, where the 1984 value is 100.

¹⁰ There is a debate in empirical studies that SoA should not be smaller than negative one. However, we believe that it should be in the range of (-2,0). The concept of SoA is the same as the concept of autoregressive coefficient in the ADF unit root test equation in the first differenced form as explained in Enders (2015, 374, 377-378). Enders (2015, 205) notes that stationarity holds if the autoregressive coefficient is the interval of (-2,0). Olczyk and Kordalska (2016), Shittu et al. (2015), Loayza and Ranciere (2005) among others find SoA to be smaller than a negative one.

¹¹ Note that the industrial electricity price has been increased to 2093.4 SAR/toe in 2016. It was 1744.5 SAR/toe in 2015.

¹² We use FMOLS here. Though the use of Dynamic OLS (DOLS) could be considered, we do not do so here because ARDL as a dynamic estimator outperforms DOLS and we already use it as a main estimator. We consider it here to compare the results from the dynamic estimator, i.e., ARDL, with those from the static estimator, i.e., FMOLS.

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Notes

Notes

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

Notes

About the Author

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Fakhri Hasanov is a Research Fellow at KAPSARC leading the KAPSARC Global Energy Macroeconometric Model (KGEMM) project. Previously he was an Associate Professor and Director of the Center for Socio-Economic Research at Qafqaz University, Azerbaijan. He holds a Ph.D. in Econometrics from Azerbaijan State University of Economics and post-doctoral study from George Washington University. His research interest and experience span econometric modeling and forecasting: building and applying macroeconometric models for policy purposes; and energy economics, with a particular focus on natural resource-rich countries.

About the Project

The objective of the KAPSARC Global Energy Macroeconometric Model (KGEMM) project is to develop a domestic policy analysis tool that captures the interactions between the Saudi and global economies. Commonly available models are typically more focused on the global economy (and the major contributors to global GDP), using an oversimplified representation of major oil and gas exporting economies to capture energy flows into the global system. They fail to take into account the importance of the energy sector in the Kingdom or the growing importance of the domestic Saudi economy as a driver of domestic demand and, hence, available oil exports.

KGEMM covers the real, monetary, fiscal, external, energy and labor sectors of the Saudi economy. It takes a demand-side view of the economy with some supply-side representations.

KGEMM has been developed by KAPSARC for the following purposes:

- To provide a representation of the Saudi economy that takes into account the special features of the Saudi economy;
- To offer KAPSARC's stakeholders a macroeconometric model to evaluate different policy scenarios such as energy price reforms, fiscal policy changes and the impacts of different oil price regimes;
- To connect KSA's macroeconomic-energy environment with the models of the global economy.

The main characteristics of KGEMM are:

- A sound theoretical foundation coupled with a representation of the special features of the Saudi economy;
- Estimations based on cutting-edge econometric methods in developing and enhancing the model;
- Ease of customization so that it can address future research/policy questions.

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