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Modelling industrial energy demand in Saudi Arabia

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ABSTRACT

Between 1986 and 2016, industrial energy consumption in Saudi Arabia increased by tenfold, making it one of the largest end-use sectors in the Kingdom. Despite its importance, there appear to be no published econometric studies on aggregate industrial energy demand in Saudi Arabia. We model aggregate industrial energy demand in Saudi Arabia using Harvey's (1989) Structural Time Series Model, showing that it is both price and income inelastic, with estimated long-run elasticities of −0.34 and 0.60, respectively. The estimated underlying energy demand trend suggests improvements in energy efficiency starting from 2010.

Applying decomposition analysis to the estimated econometric equation highlights the prominent roles of the activity effect (the growth in industrial value added) and the structure effect (the shift towards energy-intensive production) in driving industrial energy demand growth. Moreover, the decomposition shows how exogenous factors such as energy efficiency helped mitigate some of that growth, delivering cumulative savings of 6.8 million tonnes of oil equivalent (Mtoe) between 2010 and 2016.

Saudi Arabia implemented a broad energy price reform program in 2016, which raised electricity, fuel, and water prices for households and industry. The decomposition results reveal that, holding all else constant, higher industrial energy prices in 2016 reduced the sector's energy consumption by 6.9 %, a decrease of around 3.0 Mtoe. Saudi policymakers could therefore build on the current policy of energy price reform and energy efficiency standards to mitigate the rate of growth of industrial energy consumption, increase economic efficiency, and maintain industrial sector competitiveness.

1. Introduction

In Saudi Arabia, the industrial (or manufacturing[1]) sector accounted for 30.3 % of total final energy consumption in 2016, according to the IEA (2018a). Including non-energy use, which is mainly feedstock for the petrochemical sub-sector, lifts this share to over 50 %, highlighting the huge proportion of final energy consumed by the Saudi industrial sector.

Saudi Arabia's industrial sector experienced rapid growth over the last several decades. According to Saudi Arabian Monetary Agency (SAMA) (2018), industrial value added grew from 28.3 billion 2010 Saudi Riyals (SR), equivalent to 7.5 billion 2010 United States Dollars (USD), in 1986 to 213.4 billion 2010 SR in 2016, equivalent to 56.8 billion 2010 USD. This translates into a real average annual growth rate of 7 %, highlighting the pace of development in Saudi Arabia's industrial base. During this period, industrial energy consumption grew at an even faster rate of almost 8 % per annum (IEA, 2018a).

The abundance of oil and natural gas in Saudi Arabia has allowed the government to provide energy to the industrial sector at relatively low administered prices. These low energy prices appear to have influenced both the levels of energy efficiency in Saudi industry and its structure. The Heckscher-Ohlin theorem on specialization states that a country will specialize in the export of commodities that are produced with the factor of production that it possesses in relative abundance (Heckscher, 1919; Ohlin, 1933). According to this theorem, Saudi Arabia's specialization in energy-intensive exports would thus be a natural outcome of its fossil fuel endowments.

Developing a deeper understanding of industrial energy demand and its determinants is crucial to policymakers' economic plans. However, as noted by Greening et al. (2007), the industrial

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[1] Note that although not technically the same the terms 'manufacturing' and 'industry' are used interchangeably. The IEA (2018a) uses the term 'industry', in which they include sub-sectors such as chemicals, metals, and non-metallic minerals, but exclude refining, which the IEA (2018a) considers to be part of the 'transformation' sector. In contrast, Saudi Arabian Monetary Agency (SAMA) (2018) uses the term 'manufacturing', in which it includes the refining sub-sector. In this paper, we use both terms interchangeably but always exclude refining.

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sector is "one of the hardest end-uses to analyse, model, and forecast" (p. 599). Not surprisingly, we found no econometric studies published on aggregate industrial energy demand in Saudi Arabia, and very few studies on the Middle East. This implies a lack of energy elasticity estimates in the literature, a gap this paper aims to fill.

The rest of the paper is structured as follows. Section 2 presents a literature review. Section 3 discusses the Saudi data and provides a brief background on Saudi industry. It also presents the econometric and decomposition methods that are employed in the analysis. Section 4 presents the preferred estimated energy demand equation and the decomposition results. Finally, Section 5 summarizes and concludes.

2. Literature review

2.1. Econometric modelling of industrial energy demand

Econometric modelling of energy demand is often conducted for an economy or sector and can focus on aggregate energy or on specific fuels or energy carriers, such as gasoline, electricity, and natural gas. In almost all economies around the world, the end-use sectors consuming the largest shares of final energy include residential, transport, and industrial. Many econometric studies have modelled energy demand in the residential and transport sectors, but as observed by Bernstein and Madlener (2015), econometric studies of industrial energy demand and estimated elasticities remain scarce. One explanation for this, suggested by Greening et al. (2007), is that modelling industrial energy demand is relatively difficult given that different firms consume different fuels in different processes to produce a wide range of goods and services, heterogeneity that can lead to aggregation issues. The required data can also be difficult to find.

Many of the earliest econometric studies on industrial energy demand followed the seminal work of Berndt and Wood (1975). These studies often modelled a production (or cost) function with capital, labour, energy, and intermediate materials as inputs into the production process, focusing on factor substitution. More recently, several studies have employed the single-equation approach to modelling industrial energy demand. As noted by Adeyemi and Hunt (2007), the single-equation approach has become the standard approach because of "its simplicity, straightforward interpretation, and limited data requirements" (p. 694). Furthermore, Pesaran et al. (1998) discussed how the single-equation approach generally outperforms more complex approaches when modelling energy demand in a wide range of settings. In the case of Saudi Arabia (and many developing countries), the single-equation approach is particularly useful given the data limitations and is therefore employed in this paper.

When formulating econometric models of industrial energy demand, with the goal of estimating price and income elasticities, it is important that the econometric models capture the impact of exogenous factors such as technical progress. As noted by Hunt et al. (2003), for single-equation estimates some attempts to model technical progress relied on simple linear deterministic trends. Instead, Hunt et al. (2003) argued that using Harvey's (1989) Structural Time Series Model (STSM), which can accommodate a non-linear stochastic trend known as the Underlying Energy Demand Trend (UEDT), can result in more realistic energy demand models. The UEDT captures how exogenous factors unrelated to price and income affect energy demand. These factors include energy efficiency and changes in consumer behaviour, variables for which there is often no data available. Hunt et al. (2003) showed that "when compared to estimates from the more conventional cointegration technique, the structural time series model results are clearly superior" (p. 115). Hunt et al. (2003) and Dimitropoulos et al. (2005) therefore used Harvey's (1989) STSM with an autoregressive distributed lag specification to model aggregate energy demand for the UK manufacturing sector (as well as for the whole economy, residential, and transportation sectors) using quarterly and annual data, respectively. Agnolucci (2010) also estimated an energy demand function for the UK industrial sector (and the domestic sector), testing three different models in an attempt to best capture technical progress: a model with a linear deterministic trend, a model with price decomposition, and the STSM. Agnolucci (2010) found the STSM "to be an effective approach in the estimation of the energy demand" and that "future applied studies would benefit from implementing STSMs" (p. 130). This paper therefore employs the STSM to estimate an energy demand function for the industrial sector in Saudi Arabia.

To the best of our knowledge, there are no studies published on the econometric modelling of aggregate industrial energy demand in Saudi Arabia, whether individually or as part of a panel. There are a few studies however that focus on industrial electricity demand (which in Saudi Arabia is a small proportion of total industrial energy demand), and are somewhat dated, having been published before the year 2000. Looking at the wider Middle East region, we found no studies of aggregate industrial energy demand, and only a handful of studies that modelled industrial electricity demand only (see Table 1).[2] The studies in Table 1 suggest that industrial electricity demand in Saudi Arabia is price and income inelastic, and that it is also price inelastic for the wider Middle East region. The studies also reveal income elastic industrial electricity demand in Israel and Egypt. However, none of these studies provide a good indication of the elasticities of aggregate industrial energy demand or industrial demand for other fuels such as natural gas, which accounts for the largest share of industrial energy demand in many Middle Eastern countries (IEA, 2018a).

2.2. Decomposition analysis of industrial energy consumption

To better understand the drivers of industrial energy demand, we augment the estimated econometric equation by using decomposition analysis to quantify the relative contributions of the drivers. Decomposition analysis is a technique that is employed to quantify the drivers or determinants of a change in an aggregate economic, environmental, or energy-related indicator (Ang and Zhang, 2000). Many of the studies that decomposed industrial energy consumption relied on the same conventional approach: energy consumption was expressed as the product of three factors using an identity. The change in energy consumption between a reference year and an end year was then decomposed into three drivers: an activity effect, a structure effect, and an intensity effect (Ang et al., 1998). Many of the decomposition methods however left a decomposition residual. Ang et al. (1998) discussed this problem introducing the Logarithmic Mean Divisa Index (LMDI) method. This method results in what is commonly referred to as a perfect decomposition that does not generate any decomposition residuals. LMDI appears to have become the preferred method for decomposition analysis, as noted by Ang (2005) and Ang (2015).

This paper applies decomposition analysis to an econometrically estimated energy demand equation to quantify the contributions of the drivers. By decomposing an estimated equation that includes several independent variables, a greater number of drivers can

[2] There have been many studies published that modelled residential electricity and gasoline demand in Saudi Arabia using a variety of econometric approaches. In fact, the STSM has been used recently to model both Saudi residential electricity (Atalla and Hunt, 2016) and gasoline (Atalla et al., 2018) demand. This paper thus complements those two studies by applying the STSM to the Saudi industrial sector.

Table 1
Previous industrial energy demand studies on the Middle East. Note: SR and LR denote short-run and long-run, respectively.

Study	Fuel	Study Period	Country	Price Elasticity		Income Elasticity	
				SR	LR	SR	LR
Al-Sahlawi (1999)	electricity	1975-1996	Saudi Arabia	–	–	0.08	0.66
Beenstock et al. (1999)	electricity	1973-1995	Israel	–	−0.31	–	1.12
El-Shazly (2013)	electricity	1982-2010	Egypt	–	0.05	–	1.33
Eltony and Mohammad (1995)	electricity	1975-1989	Saudi Arabia	−0.13	−0.20	0.60	0.89

be generated through the decomposition. Furthermore, applying decomposition analysis to an econometric equation instead of an identity allows the drivers to influence energy demand non-proportionally, assuming a log-log model where the estimated elasticities are not equal to one.

Broadstock and Hunt (2010) decomposed an econometrically estimated energy demand equation for UK transport oil demand by taking advantage of the log-log specification. Broadstock and Hunt (2010) took the difference of the log of energy demand (which approximates the percentage change in energy demand) and decomposed this into drivers: a price effect, an income effect, an efficiency effect, and an aggregate effect that captures the impact of other exogenous factors. The decomposition was done by multiplying the differences in the log of the independent variables by their corresponding estimated coefficients. This approach yields a decomposition in percentage units. In contrast, we convert the preferred estimated econometric equation back into multiplicative form and then apply additive LMDI. This delivers decomposition results in physical energy units (such as tonnes of oil equivalent, or toe), which are easier to interpret.

3. Methods

Aggregate industrial energy demand (E_t) is modelled as a function of the real gross value added by the sector (GVA_t), the real average energy price for industry (P_t), a 'structural factor' that captures how specialized Saudi Arabia is in energy-intensive exports (SF_t), and an underlying energy demand trend ($UEDT_t$), which captures the impact of exogenous factors such as energy efficiency on industrial energy demand.

3.1. Data

Energy consumption data were obtained from the IEA (2018a). Fig. 1 shows that between 1986 and 2016, aggregate energy consumption in the Saudi industrial sector grew from 4.5–42.3 million tonnes of oil equivalent (Mtoe). Fig. 1 also shows the breakdown by fuel type, highlighting the dominant role that fossil fuels play.[3]

Fig. 1 shows the existence of a discontinuity in the energy consumption data that occurred in 1990. In fact, according to the IEA's (2018b) country note on Saudi Arabia: "New data became available in 2015 allowing the estimation of natural gas consumption as a feedstock in ammonia and methanol manufacture from 1990 to 2013. The remaining natural gas consumption has been allocated to the non-specified industry sector. Breaks in time series may occur between 1989 and 1990 for this reason." This discontinuity in the data is therefore accounted for in the estimated econometric equations.

We used value added as a measure of the industrial sector's economic activity. Data on gross value added by the manufacturing sector were obtained from Saudi Arabian Monetary Agency (SAMA) (2018) and are shown in Fig. 2. The data reveal the rapid economic development that occurred in Saudi Arabia, as the sector's gross value added grew from 28.3 billion 2010 SR in 1986 to 213.4 billion in 2016.

Time series data on sub-sectoral energy consumption and sub-sectoral value added do not (yet) exist. Thus, energy demand cannot currently be modelled for industrial sub-sectors nor disaggregated by fuel type. Nevertheless, estimating elasticities for sub-sectors of Saudi industry (petrochemicals, iron and steel, cement, etc.) by fuel type will likely be an important area of research in the future as the data becomes available.

Data on energy prices were obtained from Aramco (2018). Energy prices in Saudi Arabia are set at low administered levels (at levels considerably below international market prices) and often remain fixed for long periods of time. These prices can only change through a decision by the Saudi Council of Ministers. The price of energy consumed in industry was calculated using a weighted average of fuel prices, in which the weights represented the share of industrial consumption by each fuel. The weighted average energy price was then deflated using the sector's deflator, which was obtained from GASTAT (2018). The fuels used in the industrial sector in Saudi Arabia include crude oil, diesel, heavy fuel oil, and natural gas, in addition to electricity and other refined oil products. Fig. 3 shows the evolution of the average real energy price for the industrial sector, and highlights years during which energy price reforms were implemented (as shown by the 2016 data point in Fig. 3).

The structural factor, which reflects the degree to which Saudi Arabia is specialized in energy intensive exports, was calculated using export data from CEIC Data (2018). The structural factor was calculated by taking the share of chemical, plastic and rubber, metal, and non-metallic mineral exports in total exports (excluding crude oil). These product groups are often labelled as energy intensive, and thus growth in the structural factor would reflect a shift towards energy intensive exports (and thus manufacturing). Fig. 4 shows the evolution of total exports (excluding crude oil) in Saudi Arabia between 1986 and 2016, which grew from 20 billion to over 260 billion riyals. During this period, there was a clear shift towards energy intensive exports, whose share grew from 11 % to 46 % by 2016.

3.2. Econometric modelling of industrial energy demand

The general unrestricted model (GUM) for aggregate industrial energy demand is given by the following dynamic autoregressive distributed lag specification:

$$e_t = \alpha_1 e_{t-1} + \alpha_2 e_{t-2} + \beta_0 gva_t + \beta_1 gva_{t-1} + \beta_2 gva_{t-2} + \gamma_0 p_t + \gamma_1 p_{t-1} + \gamma_2 p_{t-2} + \delta_0 SF_t + \delta_1 SF_{t-1} + \delta_2 SF_{t-2} + UEDT_t + \varepsilon_t \quad (1)$$

The variables e_t, gva_t, and p_t are the natural logarithms of E_t, GVA_t, and P_t in year t, respectively, and ε_t is a random white noise error term.

A two-year lag, which is considered reasonable given the 30-year time horizon, is employed to capture any possible dynamic

[3] The electricity consumed by industry was generated by the Saudi Electricity Company in plants that consumed natural gas, heavy fuel oil, or crude oil. Renewables currently play a negligible role in the Saudi power sector.

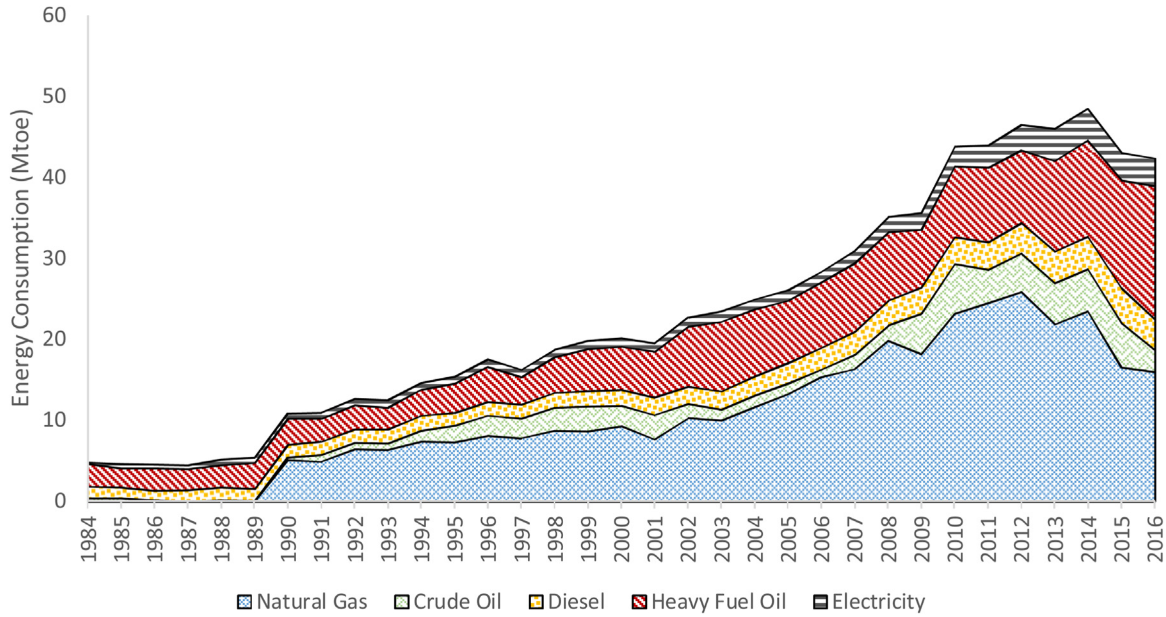

Fig. 1. Total energy consumption in the industrial sector by fuel type.

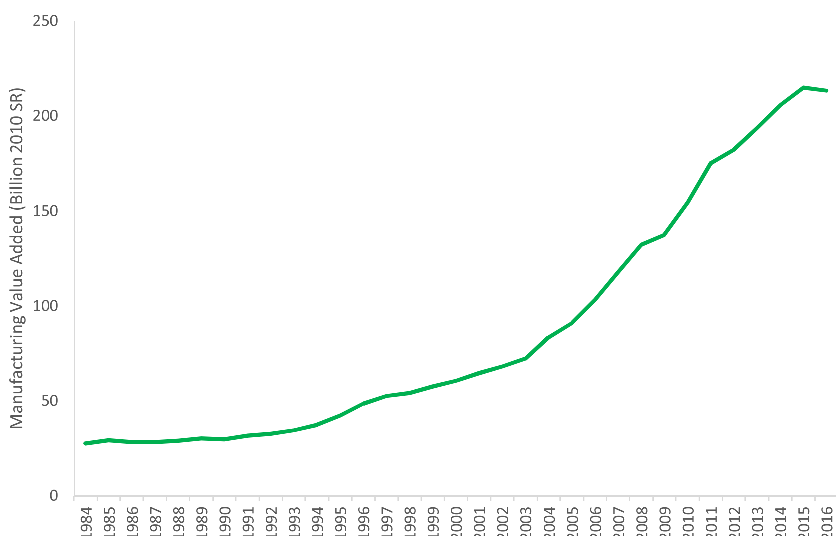

Fig. 2. Gross value added by the Saudi industrial sector.

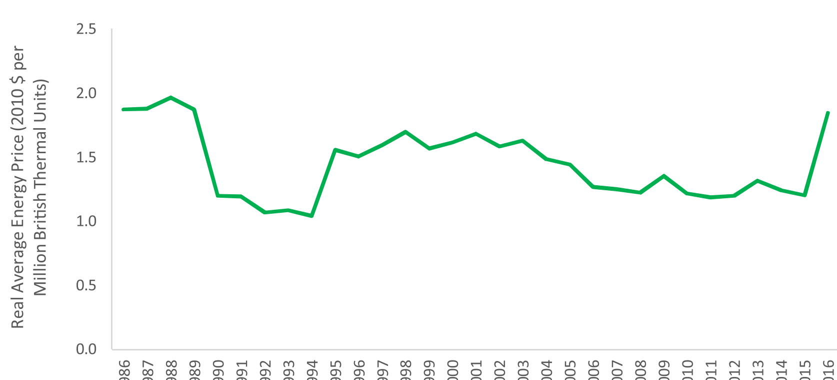

Fig. 3. The real weighted average energy price for the industrial sector.

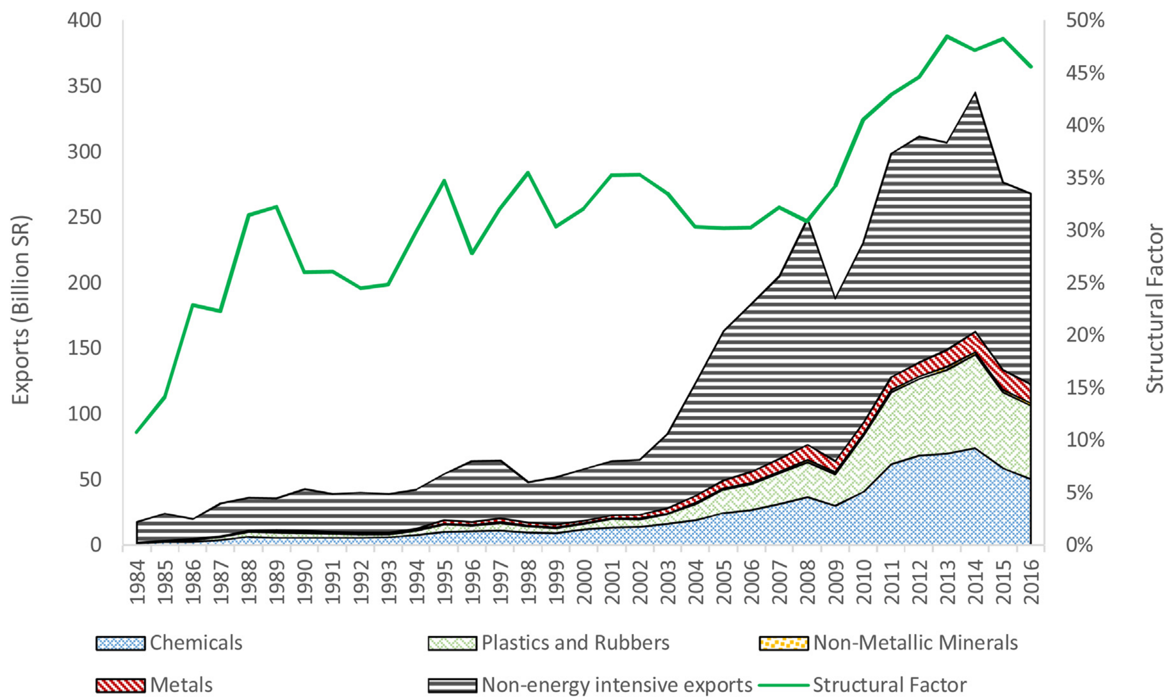

Fig. 4. Total exports and the structural factor. Notes: The structural factor is the ratio of energy intensive exports to total exports. Crude oil excluded from total exports.

effects. The coefficients β_0 and γ_0 represent the short-run (impact) elasticities for gross value added and price, respectively. The coefficient δ_0 reflects the short-run impact of economic structure on energy demand (the structural factor is the only independent variable that is not measured in logs). The corresponding long-run income, price, and structure coefficients are given by $\beta = \frac{\beta_0+\beta_1+\beta_2}{1-\alpha_1-\alpha_2}$, $\gamma = \frac{\gamma_0+\gamma_1+\gamma_2}{1-\alpha_1-\alpha_2}$, and $\delta = \frac{\delta_0+\delta_1+\delta_2}{1-\alpha_1-\alpha_2}$, respectively.

The stochastic trend is estimated through the STSM as follows:

$$\mu_t = \mu_{t-1} + \rho_{t-1} + \eta_t;\ \eta_t \sim NID(0, \sigma_\eta^2) \tag{2}$$

$$\rho_t = \rho_{t-1} + \xi_t;\ \xi_t \sim NID(0, \sigma_\xi^2) \tag{3}$$

The parameters μ_t and ρ_t are the level and slope of the stochastic trend, respectively, which together determine the shape of the UEDT (Harvey and Shephard, 1993). The hyper-parameters η_t and ξ_t are the mutually uncorrelated white noise disturbances with zero means and variances σ_η^2 and σ_ξ^2, respectively.

Equations (1)–(3) are estimated by a combination of maximum likelihood and the Kalman filter using the software package STAMP 8.30 (Koopman et al., 2007). When necessary, irregular/outlier interventions (IRR), level interventions (LVL), and/or slope interventions (SLP) are added to the model to improve the fit and help ensure it passes an array of diagnostic tests for the standard and auxiliary (irregular, level, and slope) residuals. Moreover, the interventions provide information about important breaks and structural changes during the estimation period (Harvey and Koopman, 1992). The estimation strategy thus involves initially estimating the GUM given by Eqs. (1)–(3) and then eliminating insignificant variables and adding interventions but ensuring the model passes an array of diagnostic tests[4] until the preferred parsimonious model is obtained. In other words, we follow the general-to-specific approach to obtaining the preferred model.

[4] With 10 % normally being the maximum level to reject the null hypothesis for individual parameter coefficients, interventions, and diagnostic tests.

Interventions can change the shape of the UEDT, and in their presence, the UEDT is given by the following equation according to Dilaver and Hunt (2011):

$$\begin{aligned} UEDT_t = {} & \mu_t + \text{irregular interventions} + \text{level interventions} \\ & + \text{slope interventions} \end{aligned} \tag{4}$$

As noted by Hunt et al. (2003), the stochastic UEDT captures the impact of exogenous factors, such as technical progress, improvements in energy efficiency, and changes in consumer tastes and preferences, on energy demand that are unlikely to have a constant linear effect, which is what is implicitly assumed by the inclusion of a time trend. The UEDT is therefore the preferred approach to capturing the impact of these exogenous factors since the UEDT is a flexible trend that can be linear or non-linear. This arguably allows models that incorporate the UEDT to provide more realistic results, particularly when these exogenous factors have a non-systematic impact on energy demand.

3.3. Decomposition of the estimated energy demand equation

We use additive LMDI to decompose the change in energy consumption between a reference year and an end year into additive components that we refer to as drivers. To use additive LMDI, Eq. (1) is converted into its multiplicative form by taking the exponential of both sides of the equation. This allows the estimated GUM for aggregate industrial energy demand (in physical energy units) to be expressed as follows:

$$\begin{aligned} E_t = {} & E_{t-1}^{\hat{\alpha_1}} E_{t-2}^{\hat{\alpha_2}} GVA_t^{\hat{\beta_0}} GVA_{t-1}^{\hat{\beta_1}} GVA_{t-2}^{\hat{\beta_2}} P_t^{\hat{\gamma_0}} P_{t-1}^{\hat{\gamma_1}} P_{t-2}^{\hat{\gamma_2}} * \\ & \exp(\hat{\delta_0} SF_t) \exp(\hat{\delta_1} SF_{t-1}) \exp(\hat{\delta_2} SF_{t-2}) \exp(\widehat{UEDT}_t) \exp(\hat{\varepsilon}_t) \end{aligned} \tag{5}$$

The estimated GUM expresses energy demand as a product of 13 different factors. Using the general-to-specific methodology to obtain the preferred model will likely yield a model with a smaller number of factors. Nevertheless, if we apply additive LMDI to the GUM then we would decompose the change in energy consumption between a reference year (denoted by the subscript a) and an end year (denoted by the subscript b) into 13 drivers as follows.

$$E_b - E_a = \Delta E_{E_{t-1}} + \Delta E_{E_{t-2}} + \Delta E_{GVA_t} + \Delta E_{GVA_{t-1}} + \Delta E_{GVA_{t-2}} + \Delta E_{P_t} + \Delta E_{P_{t-1}} + \Delta E_{P_{t-2}} + \Delta E_{SF_t} + \Delta E_{SF_{t-1}} + \Delta E_{SF_{t-2}} + \Delta E_{UEDT_t} + \Delta E_{\varepsilon_t} \quad (6)$$

Where the term ΔE_{x_t} reflects the contribution of variable x_t on the change in energy consumption between the reference and end years.

Contemporaneous and lagged variables can be combined (for example: $\Delta E_{price} = \Delta E_{P_t} + \Delta E_{P_{t-1}} + \Delta E_{P_{t-2}}$) to reduce Eq. (6) to the following:

$$E_b - E_a = \Delta E_{laggd} + \Delta E_{activ} + \Delta E_{price} + \Delta E_{struc} + \Delta E_{UEDT} + \Delta E_{resid} \quad (7)$$

The term ΔE_{laggd} is defined as the lagged dependent variable effect, which captures the contribution of changes in the lagged dependent variables on the change in energy consumption. The term ΔE_{activ} is defined to be the activity effect, which captures the contribution of changes in activity, measured by gross value added, to the change in energy consumption. The term ΔE_{price} is defined to be the price effect, which captures the contribution of changes in prices to the change in energy consumption. The term ΔE_{struc} is defined to be the structure effect, which captures the contribution of changes in the economic structure of industry to the change in energy consumption. The term ΔE_{UEDT} is defined to be the UEDT effect, which captures the contribution of changes in exogenous factors (such as energy efficiency but also discontinuities in the data) to the change in energy consumption. Finally, the term ΔE_{resid} is defined to be the residual effect (or error term effect), which reflects the contribution of changes in the residuals/error terms to the change in energy consumption. For models with a high coefficient of determination, the residuals are small and thus the residual effect is negligible.

Table 2
The GUM and preferred model. Note: The *, **, and *** represent statistical significance at the 10 %, 5 %, and 1 % level, respectively.

	GUM	Preferred Model
Estimated Coefficients		
α_1	−0.02201	–
α_2	−0.02121	–
β_0	0.46196	0.60022***
β_1	−0.08503	–
β_2	0.29190	–
γ_0	−0.12212	−0.18325*
γ_1	0.12584	–
γ_2	−0.29732**	−0.15669**
δ_0	0.63719*	–
δ_1	0.33860	0.67164**
δ_2	0.09527	–
Estimated Long-Run Coefficients		–
Income (Elasticity)	0.64	0.60
Price (Elasticity)	−0.28	−0.34
Structure	1.03	0.67
Hyper-Parameters		
Level	0.000000	0.000352050
Slope	0.000184836	6.97848e-005
Irregular	0.00158469	0.00137767
Interventions	LVL1990***	LVL1990*** IRR2015*
Goodness of Fit		
p.e.v.	0.0020085	0.0023648
AIC	−5.2426	−5.4664
R^2	0.99774	0.99639
R^2_d	0.94025	0.90482
Residual Diagnostics		
Std Error	0.044816	0.048630
Normality	1.9859	1.0847
H(h)	$H_{(5)}$ = 1.0553	H(6) = 2.1168
r(1)	−0.31873**	−0.063756
r(2)	0.10519	−0.010035
r(3)	−0.11606	−0.22444
Q(p, d)	$\chi^2_{5,3} = 3.2739$	$\chi^2_{5,3} = 2.0977$
r(q)	r(5) = -0.043059	r(5) = 0.12556
Auxiliary Residuals:		
Normality – Irregular	1.6213	0.62668
Normality – Level	0.54206	2.6622
Normality – Slope	0.48897	1.1162
Prediction Failure	$\chi^2_8 = 9.9455$	$\chi^2_7 = 9.9265$

4. Results and discussion

4.1. Econometric results

Following the estimation strategy outlined in the Methods section, the GUM was first estimated for the full period 1986–2016 (see Table 2). The general-to-specific methodology was then used to obtain the preferred parsimonious model for this time period, which is also shown in Table 2. Table 2 also lists the results of the summary statistics and residual diagnostics tests, which include p.e.v. (the prediction error variance), AIC (the Akaike information criterion), R^2 (the coefficient of determination), and ${R_d}^2$ (the coefficient of determination based on differences). All the normality tests are based on the Bowman-Shenton test distributed approximately as χ^2_2, while $H_{(h)}$ is the test for heteroscedasticity, distributed approximately as $F_{(h,h)}$. These are complemented by the residual autocorrelation coefficients at lag 1 $r_{(1)}$, lag 2 $r_{(2)}$, and lag 3 $r_{(3)}$, distributed approximately as N(0, 1/T), and $Q_{(p,d)}$, which is the Box-Ljung statistic based on the first p residuals' autocorrelations and distributed approximately as χ^2_d. Finally, there is the predictive failure test χ^2_f for the last eight years of the estimation period, distributed approximately as χ^2_8. Table 2 reveals that the preferred model passed all the diagnostic tests. Further details on the process used to find a preferred model and additional robustness tests can be found in Appendix A.

The explanatory variables in the estimated model are assumed to be exogenous. It can be difficult to test directly for exogeneity, but, as noted by Harvey (1989), "exogeneity can…be tested indirectly since if it does not hold, the model is unlikely to be stable and this is likely to show up when it is subjected to diagnostic checking" (p. 376). The preferred estimated model passed all diagnostic checks and demonstrated robustness (see Appendix A for additional robustness tests).

The preferred estimated model reveals that industrial energy demand is somewhat income inelastic, with a short- and long-run elasticity of 0.60. Additionally, demand is revealed to be price inelastic, both in the short and long run. The short-run (impact) price elasticity is found to be −0.18, which reflects the response of firms to a price change in the same year. The long-run price elasticity is found to be −0.34, which reflects the net response of firms to a price change over a two-year period. Comparing the long-run price elasticity for industry (−0.34) in Saudi Arabia to the price elasticity for residential electricity (−0.16) from Atalla and Hunt (2016) and the price elasticity for gasoline (−0.09 to −0.15) from Atalla et al. (2018) reveals that industrial energy demand is considerably more price elastic in comparison. Firms in Saudi Arabia thus appear to be more responsive to energy price changes than households.

Comparing our estimated long-run price elasticity (−0.34) to those estimated by Al-Sahlawi (1999) and Eltony and Mohammad (1995) of −0.31 and −0.20, respectively, reveals that our estimate is slightly more price elastic, although both of their estimates were for industrial electricity demand only. On the other hand, our estimated long-run income elasticity (0.60) is slightly more inelastic than their estimates of 0.66 and 0.89, respectively. Nevertheless,

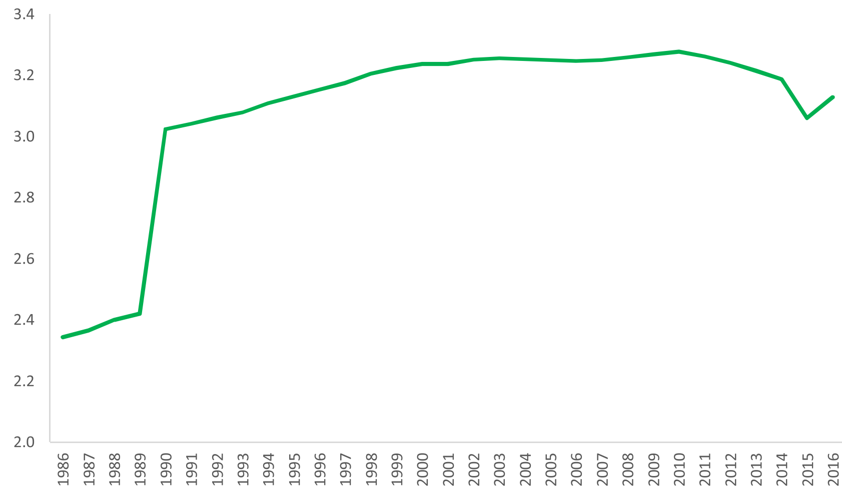

Fig. 5. The estimated UEDT for the preferred model.

our estimated elasticities for aggregate industrial energy demand are largely similar to the elasticities estimated by Al-Sahlawi (1999) and Eltony and Mohammad (1995) for industrial electricity demand only.

The preferred estimated model also reveals that economic structure has a significant impact on energy demand, with a long-run coefficient of 0.67. This underscores the impact a change in economic structure can have on industrial energy demand. This coefficient however should not be interpreted as an elasticity since the structural factor does not enter the equation in logarithms. Instead, the coefficient suggests that a 10 percentage point increase in the structural factor variable would lead to a 6.7 % increase in aggregate industrial energy demand.

Fig. 5 shows the estimated UEDT for the preferred model. In econometric studies of energy demand incorporating a stochastic UEDT but with the explanatory variables price and income only, the UEDT will likely capture exogenous factors including energy efficiency and economic structure. However, because we made the effect of structure endogenous through the inclusion of the structural factor as an independent variable in the model, the UEDT should largely reflect changes in energy efficiency (although not exclusively). Fig. 5 shows that the UEDT was upward sloping or flat up to 2010, hinting at a lack of energy efficiency improvement during this period. From 2010 onwards, the UEDT became downward sloping with a negative derivative, suggesting a growing role for energy efficiency in reducing industrial energy consumption in the Kingdom.

4.2. Decomposition results

Additive LMDI was used to decompose the change in energy consumption (defined through the preferred estimated equation) between reference and end years into five contributions or drivers: an activity effect, a price effect, a structure effect, a UEDT effect, and a residual effect.[5] More details on how the additive LMDI method was applied to the preferred estimated econometric equation, and how the method compares to Broadstock and Hunt (2010), can be found in Appendix B.

Fig. 6 illustrates the decomposition results, revealing that the activity effect was the largest driver of energy consumption growth in Saudi industry. The positive values for the activity effect indicate that it consistently exerted upward pressure on energy demand. In other words, the increase in industrial activity was driving industrial energy demand growth. In fact, over the course of the 31-year period, there were only three instances in which Saudi industry contracted: 1986–1987, 1989–1990, and 2015–2016. Another important driver that often exerted upward pressure on industrial energy demand was the structure effect. Positive values reflect how Saudi Arabia's move towards more energy-intensive manufacturing led to increases in energy consumption over the years. In contrast, the price effect played a limited role, with small negative and positive values observed. This is not surprising given that energy prices were largely flat (in nominal terms), with only a handful of increases and decreases scattered throughout the study period. For example, the industrial diesel price increased in 1995, contributing to lower energy consumption, hence the negative value for the price effect for 1994-1995. The reason energy prices occasionally exerted upward pressure on energy consumption is because they were decreasing in real terms even if they did remain flat in nominal terms. However, between 2015 and 2016, Saudi Arabia implemented a broad energy price reform program. This program resulted in a significant 3 Mtoe decrease in energy consumption for the industrial sector, highlighting the potential role that energy price reform can play in managing the growth of energy demand. The UEDT effect also appears to have played a limited role with only certain years being exceptions. However, the UEDT includes interventions that were added to the preferred model. In some cases, the interventions can be attributed to an easily identifiable event or cause (such as the intervention due to the discontinuity in the IEA data between 1989 and 1990). In other cases, it can be difficult to attribute an intervention to a specific event or cause, particularly when there are lags between them and their impact on a variable such as energy consumption. In any case, there were only two interventions added to the model: a level intervention in 1990 and an irregular intervention in 2015. The effect of the level intervention in 1990 appears in the decomposition results for the period 1989–1990, while the effects of the irregular intervention in 2015 appear in the decomposition results for 2014–2015 and 2015–2016.

It is possible to present the decomposition results while separating the impact of the interventions from the UEDT. This is shown in Fig. 7, which illustrates the same decomposition from Fig. 6, with the only difference being that the effect of interventions was separated from the UEDT, leaving behind only the UEDT level (that is, μ_t from Eq. (4)). The decomposition results confirm that without the interventions, the stochastic trend consistently exerted downward pressure on energy consumption from 2010 onwards. It is during this period that the Saudi government displayed increasing inter-

[5] Given the absence of a lagged dependent variable in the preferred model, there is no lagged dependent variable effect in the decomposition.

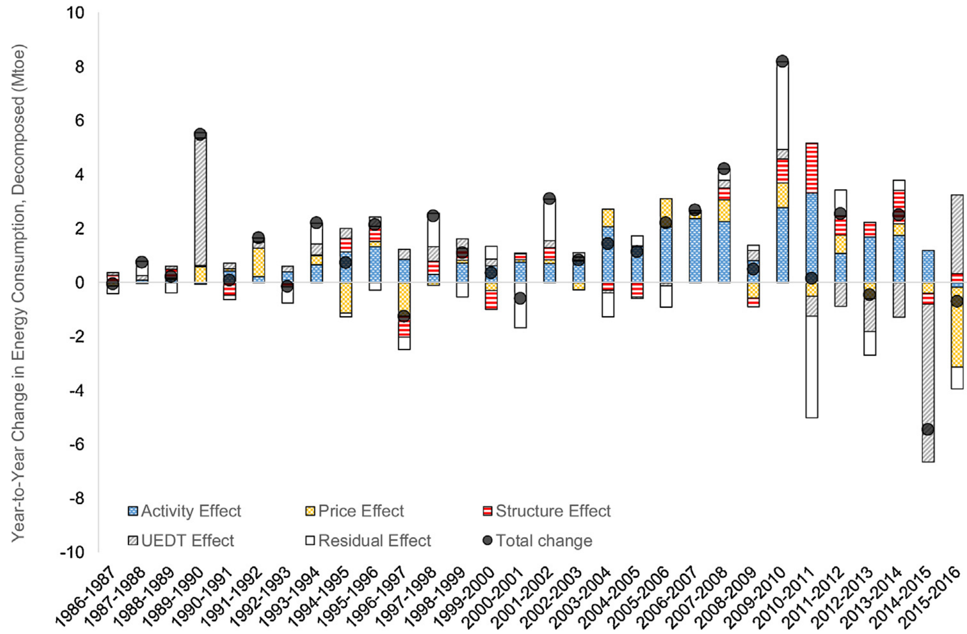

Fig. 6. The change in energy consumption (year to year) decomposed into five drivers.

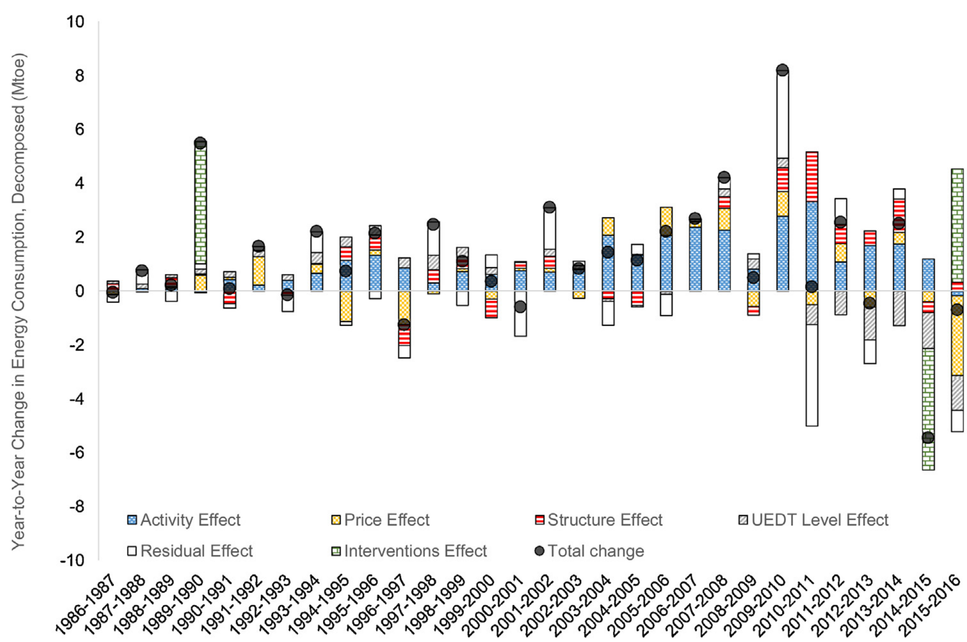

Fig. 7. The change in energy consumption (year to year) decomposed into six drivers including separated interventions.

est in energy efficiency, establishing a number of initiatives around it such as the Saudi Energy Efficiency Center and the Saudi Energy Efficiency Program.

It is useful to present the decomposition results for longer periods as well, which are illustrated in Fig. 8. These results make it possible to see the longer-term drivers of industrial energy demand. Focusing on the decomposition results for the period 2000–2016, we can see that actual energy consumption grew by 22.2 Mtoe. The activity effect, which reflects the growth in output, was the primary driver, contributing 22.6 Mtoe to this growth. The structure effect, which reflects the shift in Saudi Arabia towards energy-intensive manufacturing, contributed an additional 3.6 Mtoe. The price effect also contributed 0.7 Mtoe to this growth, even though energy prices were reformed in 2016. This is because of two reasons. First, industrial fuel prices since 2000 have remained largely flat in nominal terms, which implies that they have been decreasing each year in real terms. Therefore, even after 2016′s price reform, the average industrial energy price in 2016 was only slightly higher than in 2000 when adjusted for inflation. Second, even though real industrial fuel prices in 2016 were only slightly higher than they were in 2000, the price effect captures both differences in contemporaneous prices (that is, between 2016 and 2000) and differences in lagged prices (2014 and 1998, to be specific). The data shows that the lagged price in 2014 was far lower than in 1998, leading to the slightly positive price effect. In contrast to the activity, structure, and price effects, the UEDT level effect (which appears to be largely driven by energy efficiency) helped lessen the growth in industrial energy consumption, contributing −3.2 Mtoe. The residual effect accounted for the remainder.

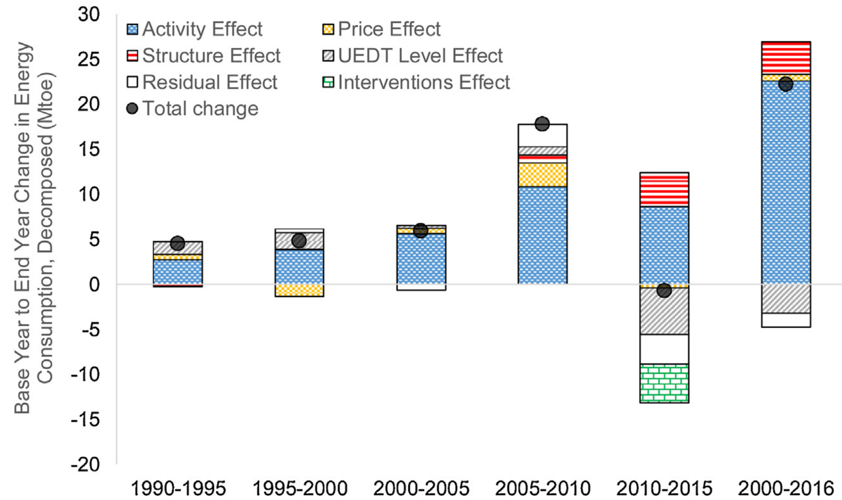

Fig. 8. The change in energy consumption between a reference year and an end year decomposed into six drivers including separated interventions.

5. Conclusions

This study is, to the best of our knowledge, the first to model aggregate industrial energy demand in Saudi Arabia econometrically and quantify the drivers of its growth. The estimated model found the long-run income and price elasticities to be 0.60 and -0.34, respectively. The long-run income elasticity suggests that Saudi Arabian industrial energy demand will continue to grow over the coming decades as economic activity expands. The long-run price elasticity however suggests potential for mitigating some of this growth through increased energy prices. The price elasticity also demonstrates that Saudi industrial firms are relatively more responsive to changes in energy prices compared to Saudi households.

The estimated econometric model also showed that Saudi Arabia could increase its industrial energy productivity substantially by moving away from energy-intensive manufacturing. The structural elasticity shows that a 10 percentage point shift away from energy-intensive exports for example could reduce industrial energy consumption by 6.7 % in the long run, holding all else fixed. This underscores the important role economic structure can play over the next decade as Saudi Arabia moves towards higher value added manufacturing.

Decomposition analysis was then applied to the estimated econometric model to quantify the drivers of the growth in industrial energy consumption in Saudi Arabia over the past several decades. The decomposition results showed that the activity effect was the primary driver. Additionally, the shift towards energy-intensive manufacturing exerted upward pressure on industrial energy consumption throughout the study period. In contrast, the UEDT effect exerted downward pressure from 2010 onwards, suggesting energy efficiency improvements, helping to mitigate some of the growth in industrial energy consumption. Finally, the decomposition analysis revealed that energy prices, which had remained largely flat over the study period, played a limited role in most years.

However, on December 29, 2015, Saudi Arabia implemented an energy price reform program, which affected households and firms across all sectors of the economy (Alriyadh, 2015). The program aims to raise domestic energy prices towards international benchmarks. The goals are to raise government revenues, stimulate greater productivity, and encourage investments that can help Saudi Arabia diversify its energy mix. The decomposition analysis showed that higher industrial fuel prices in 2016 reduced the sector's energy consumption by 6.9 %, equivalent to energy savings of around 3.0 Mtoe. Further price reforms for industrial fuels are expected over the coming years, which will likely mitigate the growth rates of industrial energy consumption in Saudi Arabia.

Although we quantify the impact of higher energy prices on consumption, our analysis does not show the possible impact on competitiveness. The relatively low energy prices in Saudi Arabia have steered domestic firms towards the production and export of energy-intensive goods. Higher energy prices would likely weaken their advantage in energy-intensive exports but may also drive them towards the production and export of higher value added goods. This already appears to be the case. The petrochemical industry for example has already started moving towards the production of higher value added chemicals (Jadwa Investment, 2017).

Since higher domestic energy prices lift government revenues, they may be combined with a subsidy scheme (or similar program) that promotes industrial energy efficiency to lessen the negative impact of higher energy prices on competitiveness. In fact, the decomposition analysis suggests that improvements in energy efficiency from 2010 onwards delivered cumulative energy savings of 6.8 Mtoe. Energy efficiency thus carries the potential to both mitigate the rapid growth in industrial energy consumption and support the competitiveness of industrial firms.

In summary, the econometric results revealed the relationships between prices, income, structure, efficiency, and energy consumption in the Saudi industrial sector, while the decomposition results showed the drivers of the growth in industrial energy consumption over the last several decades. These results suggest that policymakers could build on the current policy of energy price reform and energy efficiency standards to mitigate the rate of growth of industrial energy consumption, increase economic efficiency, and maintain industrial competitiveness.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.eneco.2019.104554.

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