Projecting Saudi Arabia's CO_2 Dynamic Baselines to 2060: A Multivariate Approach

*Abdulelah Darandary,[a] Anwar A. Gasim,[a] Lester C. Hunt,[b] and Jeyhun I. Mikayilov[a]**

ABSTRACT

Using an econometric model, we generate scenario projections of CO_2 emissions under different sets of assumptions on the underlying drivers. These drivers include GDP, the energy price, economic structure, and the underlying emissions trend. Our baseline scenario projects that Saudi CO_2 emissions will rise from 540 Mt in 2019 to 621 Mt in 2030 and 878 Mt in 2060. In a high GDP growth scenario, the corresponding numbers for CO_2 emissions are 635 Mt in 2030 and 985 Mt in 2060. In contrast, in a low GDP growth scenario, CO_2 emissions would grow to 607 Mt in 2030 and 781 Mt in 2060. In an economic diversification scenario, CO_2 emissions would grow to 602 Mt in 2030 and 769 Mt in 2060. These projections are 646 Mt and 1096 Mt for the heavy industrialization scenario. Even in our lowest scenario, further efforts are needed to meet the net zero ambition.

Keywords: CO_2 emissions, Saudi Arabia, baseline scenario, economic structure, economic growth, net-zero target

https://doi.org/10.5547/01956574.45.SI1.adar

1. INTRODUCTION

As a party to the Paris Agreement, which aims to limit the global average temperature rise to below 2 degrees Celsius and as close as possible to 1.5 degrees Celsius (Paris Agreement, 2015), Saudi Arabia has submitted a nationally determined contribution (NDC). NDCs are essentially climate action plans encompassing a party's climate target and the initiatives or policies it plans to implement to achieve that target. NDCs lie "at the heart of the Paris Agreement" and are submitted in 5-year intervals, with each successive NDC (either referred to as a new or updated NDC) reflecting higher ambition (UNFCCC, 2022).

Saudi Arabia has so far participated in two successive rounds of NDC submissions. In its first NDC, Saudi Arabia pledged to reduce its greenhouse gas (GHG) emissions by 130 million tons (Mt) of carbon dioxide equivalent (CO_2eq) annually by 2030 (Kingdom of Saudi Arabia, 2015, p. 1). In its updated NDC, Saudi Arabia more than doubled its previous goal, announcing its new pledge to

a King Abdullah Petroleum Studies and Research Center (KAPSARC), PO Box 88550, Riyadh 11672, Saudi Arabia

b School of Accounting, Economics and Finance, University of Portsmouth, Richmond Building, Portsmouth, PO1 3DE, UK

* Corresponding author. Address: King Abdullah Petroleum Studies and Research Center (KAPSARC), PO Box 88550, Riyadh 11672, Saudi Arabia, email address: Jeyhun.Mikayilov@kapsarc.org

reduce GHG emissions by 278 $MtCO_2eq$ annually by 2030 (Kingdom of Saudi Arabia, 2021, p. 2)[1]. Saudi Arabia also recently announced its ambition to achieve net zero by 2060 (Arab News, 2021).

Saudi Arabia's NDC emission target is expressed as a reduction below a baseline or business-as-usual emissions growth scenario. Vaidyula and Hood (2018) refer to such targets as baseline targets, which many developing countries appear to prefer. In contrast, other countries, especially developed countries, prefer absolute targets, which are expressed as a reduction below historical emissions in a specified base year. Baseline targets rest on developing a baseline or business-as-usual scenario, which shows how emissions would evolve if no further mitigation policies or measures were adopted (IPCC, 2022).[2]

Some countries with baseline targets have not yet publicly released quantitative information about their baselines in their NDCs (UNFCCC, 2021). However, most have provided qualitative information about the key assumptions, variables, or parameters that their baseline scenarios depend on. There are no specific requirements that need to be followed by countries when developing a baseline for their target. However, most countries appear to be using gross domestic product (GDP) and population growth as key parameters driving their baseline scenarios (UNFCCC, 2021).

The lack of quantitative baselines may stem from the difficulties of constructing baseline scenarios. As noted by Vaidyula and Hood (2018), many variables can influence a country's baseline emissions scenario. Furthermore, the choice of method used to project emissions can significantly influence its trajectory. Given these uncertainties, some parties to the Paris Agreement have released the specific modeling tools they used to estimate their baseline or business-as-usual emissions scenario (UNFCCC, 2021).

Although Saudi Arabia is one of the countries that did not yet publicly disclose a quantitative baseline in its NDC, it provided qualitative information on its baseline, which it has chosen to be a dynamic baseline (Kingdom of Saudi Arabia, 2021, p. 3). Saudi Arabia's dynamic baselines depend on the level of economic development and the extent of economic diversification that occurs in the country over the coming years. Specifically, Saudi Arabia has envisioned two distinct but possible baseline scenarios: In the first, which is taken to be the default scenario, Saudi Arabia achieves economic diversification, as oil export revenues are "channeled into investments in high value-added sectors such as financial services" and tourism. In the second scenario, oil resources are utilized domestically to expand Saudi Arabia's energy-intensive industrial base, with increasing contributions of "petrochemical, cement, mining, and metal production industries to the national economy." In its updated NDC, the Kingdom of Saudi Arabia (2021, p.4) states that the "main difference between the two baseline scenarios is the allocation of hydrocarbons produced for either domestic consumption or export." In other words, these two scenarios differ mainly in their assumptions on the future structure of the Saudi economy.

The structure of the Saudi economy is expected to play a key role in the evolution of Saudi Arabia's GHG emissions. The Saudi economy is poised to change dramatically following the launch of structural reforms in 2016 that aim to set the Kingdom on a path toward economic diversification (Saudi Vision, 2030). For example, the country has been reforming its energy prices under its Fiscal Balance Program, reducing the demand for energy and emissions and encouraging the growth of less emission-intensive industries (Fiscal Balance Program, 2019). The government has also commissioned the Public Investment Fund, its sovereign wealth fund, to invest in services sectors, such

1. The Kingdom's NDC target specifies reductions, avoidances, and removals of GHG emissions to achieve the target.

2. In their definition of baseline scenarios, the IPCC (2022) add that baseline scenarios are "not intended to be predictions of the future, but rather counterfactual constructions that can serve to highlight the level of emissions that would occur without further policy effort."

as tourism and non-oil industrial sectors (Public Investment Fund, 2018). Tourism is a relatively small sector in Saudi Arabia today. However, major development projects, dubbed Giga Projects, are expected to transform the sector in the near future (PIF Giga Projects, 2018). Further reforms and progress across multiple national programs are expected to significantly affect Saudi Arabia's economic structure and, therefore, its emissions.

This paper contributes to understanding how emissions may evolve in Saudi Arabia through 2030 and up to 2060 by producing various dynamic emissions scenarios, including a baseline scenario, demonstrating how different variables, such as GDP, the real energy price, and economic structure, influence the evolution of CO_2 emissions in Saudi Arabia. We focus on CO_2 emissions only, which account for around 80–90% of total GHG emissions in Saudi Arabia. We construct our CO_2 emissions scenarios using a preferred equation following the use of the two econometric methods, Autometrics and the Structural Time Series Model (STSM), that can explain the emissions data through a combination of trends, interventions, and right-hand side variables like GDP and energy prices—but in different ways. Based on the preferred equation, our projections show that CO_2 emissions in Saudi Arabia would grow to 621 $MtCO_2eq$ by 2030 and 878 $MtCO_2eq$ by 2060 in our central business-as-usual baseline scenario (with several alternative scenarios also constructed as discussed in detail below).

This paper is organized as follows. Section 2 presents a brief review of the relevant literature, followed by Section 3, which details the estimation methodologies, the data used in the analysis, and the scenario construction. Section 4 presents the estimation results and the scenario emission projections and Section 5 concludes and offers some policy implications[3].

2. LITERATURE REVIEW-

Climate change caused by GHG emissions lies at the heart of this paper, especially carbon dioxide (CO_2), given its substantial share in total GHG emissions. Not surprisingly, the study of CO_2 emissions is a significant part of research on environmental issues. Since countries are looking for alternative solutions to mitigate the negative impacts of CO_2 emissions, research dedicated to modeling and forecasting the potential future trajectories of CO_2 emissions encompasses a substantial portion of CO_2 emissions-related studies. To the best of our knowledge, no previous journal paper has focused on the multivariate modeling of total CO_2 emissions for Saudi Arabia using time series data. There are, however, several papers that use panel data, including Saudi Arabia. Considering the vast number of papers modeling CO_2 emissions, we review only papers that include Saudi Arabia. In addition, since the main target of this study is to construct scenario simulations/forecasts, we also focus on papers dealing with forecasting. For more general information on papers devoted to CO_2 emissions modeling and forecasting, Mitić et al. (2019) is a valuable reference.

Alkhathlan and Javid (2013) modeled Saudi Arabian CO_2 emissions caused by energy consumption, including petroleum, natural gas, and electricity, using data from 1980 to 2011. Their income elasticity of CO_2 emissions from fuel consumption is 0.45. However, Alkhathlan and Javid (2013) did not make projections, and given that their data used for estimation ended in 2011, they did not capture the behavior of CO2 emissions in recent years. In addition, they modeled only fuel-based CO_2 emissions, not total CO_2 emissions. Al-Mulali and Tang (2013) modeled CO_2 emissions for GCC countries, including Saudi Arabia, using data from 1980 to 2009, finding a Saudi-specific income elasticity of 0.07. Arouri et al. (2012) studied a similar relationship for a panel

3. Section A.1 in the Appendix explores model selection further. Moreover, Sections A2 and A3 focus on the super exogeneity and parameter stability, respectively.

of MENA countries. They concluded that there was an inverted U-shaped relationship for Saudi Arabia (with a data span of 1981–2005), which is arguably surprising given Saudi Arabia's stage of economic development. Mahmood et al. (2022), using data from 1980 to 2019, modeled CO_2 emissions for GCC countries, considering asymmetric impacts, and, for Saudi Arabia, they did not find an asymmetric impact, the coefficient being insignificant for negative income growth. However, Mahmood et al. (2022) did not undertake any forecasting. Utilizing GCC group data for 1990–2011, Omri (2013) found a monotonically increasing relationship between income and CO_2 emissions with a CO_2 income elasticity of 0.67. Omri et al. (2015), utilizing panel data from 1990–2011, modeled CO_2 emissions for GCC countries, and, unlike Omri (2013), they concluded that there was an inverted U-shaped relationship between income and CO_2 emissions for Saudi Arabia. Using panel data for OPEC member countries between 1990–2014, Onifade et al. (2020) concluded that income has an insignificant impact on CO_2 emissions for Saudi Arabia. Ozcan (2013) used data from 1990 to 2008 for the MENA countries and found an insignificant impact of income on CO_2 emissions for Saudi Arabia.

In summarizing the papers reviewed above, the average income elasticity is approximately 0.4, although the basis for these findings is arguably questionable. Furthermore, a common feature is that they did not produce projections for the future path of CO_2 emissions. In addition, they used energy consumption as a driver of CO_2 emissions, but Jaforullah and King (2017) have shown that using energy consumption to calculate CO_2 emissions and then using the same variable for modeling purposes results in biased estimation results. Moreover, according to Kennedy (2008), using some panel data techniques might result in under- or over-estimating country-specific features of relationships.

Shannak et al. (2024), using data from 1990 to 2019, modeled transport-specific CO_2 emissions for Saudi Arabia and produced forecasts until 2030 that reached 184 Mt of CO_2 emissions. However, as stated, Shannak et al. (2024) only considered transport-related CO_2 emissions.

Given the primary aim of this paper, it is useful to consider previous attempts to construct scenario projections for CO_2 emissions for Saudi Arabia; however, as far as we know, there are only three previous studies. Köne and Büke (2010) used linear trend analysis to model CO_2 emissions for the top 25 emitters, including Saudi Arabia. They made projections for low, reference, and high economic growth scenarios for CO_2 emissions by 2030, which ranged from 496 to 571 Mt. Using a Circular Carbon Economy framework, Alshammari (2020) evaluated various technological possibilities and potentials for attaining climate objectives and projected CO_2 emissions until 2050. According to their business as usual scenario, Saudi CO_2 emissions would be between 643 Mt and 2156 Mt in 2050. Based on univariate econometric estimated equations, Gasim et al. (2023) produced a baseline scenario for Saudi-specific total CO_2 emissions until 2060, suggesting that in 2030 and 2060, Saudi CO_2 emissions could be 678 Mt and 970 Mt, respectively. However, the projections in Gasim et al. (2023) were constructed specifically to provide a baseline projection, not to make simulations for policy scenarios.

This brief review of the relevant literature shows that, as far as we know, no published paper utilizes time series data estimation approaches to estimate models for projecting the potential future trajectory of Saudi Arabian CO_2 emissions under different assumptions. This paper, therefore, aims to model Saudi Arabian CO_2 emissions using a multivariate framework and then use the estimated model(s) to make policy simulations until 2060 under different scenario assumptions.

3. METHODOLOGIES AND DATA

Section 3.1 introduces the utilized estimation techniques, with a general overview in sub-section 3.1.1, an estimation procedure with Autometrics in 3.1.2, and STSM in 3.1.3. Sub-section 3.1.4 introduces the data used for estimations and discusses the variables employed. Section 3.2 provides scenario designs for the projections of CO2 emissions until 2060.

3.1 Econometric Estimation

3.1.1 Overview

We model the natural logarithm of Saudi CO_2 emissions as a function of a selection of vectors of drivers. In the general equations, one-year lags of all variables are included to capture autoregressive behavior, and a 'preferred' or 'final' equation is obtained by adding statistically significant interventions (also known as dummy variables) and dropping the insignificant right-hand side variables while monitoring an array of diagnostic tests. To estimate the various models, we consider two different econometric techniques: Autometrics[4] and the Structural Time Series Model since these both utilize a combination of trends and interventions but in very different ways.

3.1.2 Autometrics

The Autometrics multipath-search machine-learning algorithm (Doornik & Hendry, 2018) is applied to the General-to-Specific (Gets) Modelling approach (Hendry & Doornik, 2014). This approach identifies potential interventions caused by policy changes and shocks, whose omission might cause biased estimation results. It automatically assigns one-time pulse, blip, change in level, and break-in trend dummies to each observation and chooses the significant ones using the block-search algorithm. The Autometrics general specification utilized is therefore given by:

$$CO_{2_t} = \alpha_0 + \alpha_1 CO_{2_{t-1}} + \alpha_2 \boldsymbol{X}_t + \alpha_3 \boldsymbol{X}_{t-1} + \sum\nolimits_1^T \vartheta_i IIS_t + \sum\nolimits_1^{T-1} \tau_i SIS_t + \sum\nolimits_1^T \varphi_i DIIS_t + \sum\nolimits_1^T \omega_i TIS_t + \varepsilon_t \quad (1)$$

where CO_{2_t} is the natural logarithm of Saudi CO_2 emissions in the year t, $\boldsymbol{X}_t$ is a vector of drivers in the year t, IIS_t is an Impulse-Indicator, SIS_t is a Step-Indicator, $DIIS_t$ is a Differenced Impulse-Indicator, and TIS_t is a Trend-Indicator. α_i, ϑ_i, τ_i, φ_i, ω_i are regression coefficients to be estimated; and ε_t is a random error term ~ $NID\ (0,\sigma_\varepsilon^2)$.

The modeling procedure using Autometrics entails two parts (see, for example, Castle et al., 2017; Hendry, 2020). Firstly, the constant term and all the lagged values of the dependent and independent variables are fixed, allowing the algorithm to search for and choose the intervention dummies using what is referred to as a 'minute' significance level (0.01%). If, however, no interventions are found, the search is redone but with a 'tiny' significance level (0.1%), and if again no interventions are found, the search is redone with a 'small' significance level (1%) (see Hendry and Doornik (2014) on how to choose the optimal significance level). The specification that emerges from this process is regarded as the General Unrestricted Model (GUM). Secondly, the chosen dummies from the first stage are fixed, while the lagged values of the dependent and independent

4. It should be noted that Hendry (2020) took a similar approach to our Autometrics approach. He modeled UK CO_2 emissions data from 1860 to 2017 using a general-to-specific modeling approach and a multipath machine learning search technique. Hendry (2020) considered capital stock, GDP, oil consumption, and coal consumption as potential drivers of CO_2 emissions but concluded that capital stock and not GDP was an appropriate driver of UK CO_2 emissions. Furthermore, Hendry (2020) also used his preferred equation to assess the UK's 2050 CO_2 target's achievability.

variables are unfixed. A new search is undertaken to determine the final preferred specification based on the congruency criterion and multiple diagnostic tests. In this step, what is referred to as a 'huge' significance level (10%) is utilized for the search, as suggested by Castle et al. (2021). This is all undertaken using the multipath selection procedure embedded in the PcGive-15.10 econometric modeling program (Doornik & Hendry, 2018). This procedure was applied to four sets of explanatory variables outlined below, and the results are also discussed below after outlining the alternative estimation methodology, the STSM.

3.1.3 STSM

The STSM models CO_{2_t} emissions using a stochastic trend, which captures long-term movements in time series variables and can be extrapolated into the future (Harvey, 1989). For consistency, the STSM general specification is:

$$CO_{2_t} = \gamma_t + \alpha_1 CO_{2_{t-1}} + \alpha_2 \boldsymbol{X}_t + \alpha_3 \boldsymbol{X}_{t-1} + \varepsilon_t \tag{2a}$$

where CO_{2_t}, $\boldsymbol{X}_t$, and α_i are as defined above, γ_t is a stochastic trend (or time-varying intercept) and ε_t is a random error term ~ *NID* $(0,\sigma_\varepsilon^2)$. The stochastic trend is made up of a level μ_t and a slope β_t which are defined as follows:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{2b}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{2c}$$

where η_t ~ *NID* $(0,\sigma_\eta^2)$ and ξ_t ~ *NID* $(0,\sigma_\eta^2)$ are mutually uncorrelated random disturbance terms. If the variances of either η_t or ξ_t are found to be zero, that component of the trend becomes deterministic. If both hyperparameters are found to be zero, the stochastic trend collapses into a deterministic trend. Like Autometrics, dummy interventions can be identified and added to the model (Harvey & Koopman, 1992)—irregular interventions (Irr_t), level interventions (Lvl_t), and slope interventions (Slp_t)—which capture important breaks and structural changes during the estimation period at certain dates. However, unlike Autometrics, this is a manual process with the decision about which dummy interventions to consider determined by an examination of the equation residuals, the irregular residuals, the level residuals, and the slope residuals as well as diagnostic statistics such as the non-normality tests for all sets of residuals during the testing down general to specific process. The interventions included in the estimated equation can then be incorporated into the stochastic trend, which can be defined as follows:

$$\gamma_t = \mu_t + \text{irregular interventions} + \text{level interventions} + \text{slope interventions} \tag{2d}$$

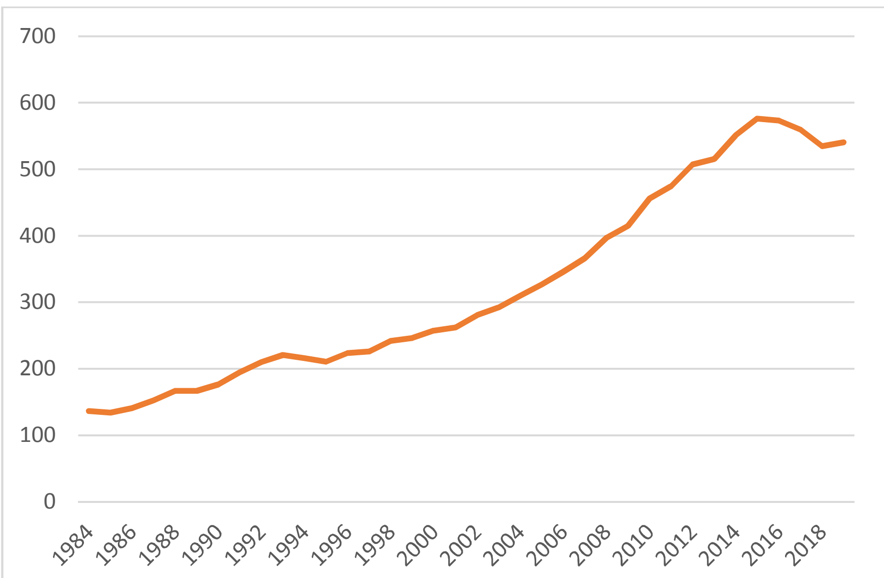
The STSM is also often referred to as the unobserved components model since the trend attempts to capture any systematic influences on the left-hand side dependent variable not captured by the right-hand explanatory variables. Hence, in this case, it represents the changes in CO_2 emissions driven by a range of unobserved exogenous or autonomous factors, such as exogenous energy and CO_2 emission factors, changes in environmental regulatory policies, increased environmental education and awareness, cultural changes, changes in preferences, etc. This interpretation of the estimated trend was coined the Underlying Energy Demand Trend (UEDT) when applied to behavioral energy demand functions (Hunt et al., 2003 and Hunt and Ninomiya, 2003) but has recently also been applied to CO_2 relationships by Javid and Khan (2020) and Guven and Kayakutlu (2020) to estimate underlying carbon emission trends and dubbed by Guven and Kayakutlu (2020) as the Underlying Emissions Trend (UET) which we use here.

To estimate the STSM, equations (2a), (2b), and (2c) are initially estimated by maximum likelihood along with the Kalman filter using the software package STAMP 8.40 (Koopman et al., 2007). Where identified, irregular, level, and/or slope interventions are included in the model and statistically insignificant variables excluded while ensuring that a range of diagnostic tests (detailed in the results below) are passed as well as ensuring that the auxiliary residuals associated with the irregular, level, and slope components do not suffer from non-normality. Consistent with the Autometrics estimation, this approach was applied to four sets of explanatory variables, and the results are discussed below.

3.1.4 Data

The data used for estimation ranges from 1990 to 2019. Data for the dependent variable, total CO_2 emissions (excluding emissions from land-use, land-use change, and forestry), are illustrated in Figure 1 and were obtained from Enerdata (2022). The independent variables considered for the $\boldsymbol{X}_t$ vector of drivers includes real GDP, sectoral value added for manufacturing, services, and agriculture, and the share of services in non-oil GDP. Real GDP data, illustrated in Figure 2, were obtained from the General Authority of Statistics (GaStat, 2021) latest release, running from 1984 to 2021.

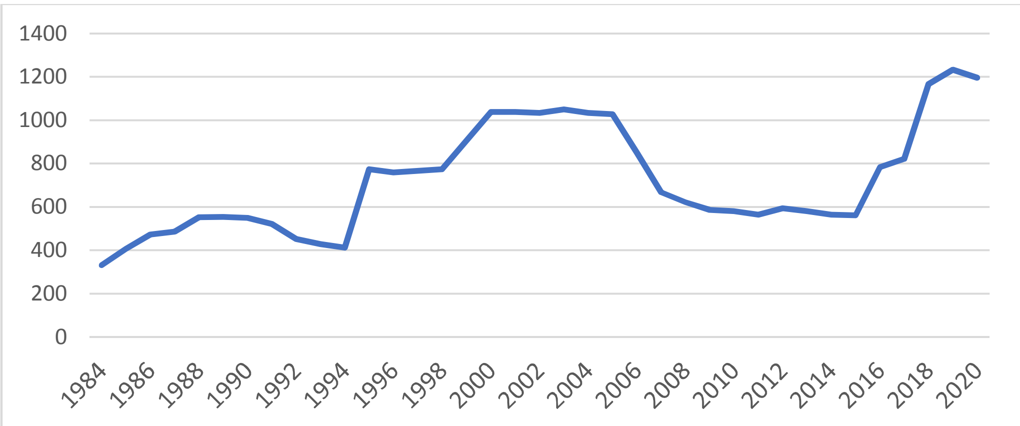
Figure 1. Total CO_2 emissions in million tons.



Source: Enerdata (2022)

The aggregate real energy price index, shown in Figure 2, was constructed in two steps. First, sectoral energy prices in Saudi Arabian Riyals (SAR) per ton of oil equivalent were obtained from Hasanov et al. (2020). Second, the index was constructed by calculating a weighted average of these sectoral energy prices, in which the weight for each sector is its contribution to gross domestic product (GDP), obtained from GaStat (2021). The index covers all sectors in the economy, including the energy end-use sectors (e.g., manufacturing and financial services) and the transformation sectors (e.g., power and refining). The aggregate energy price was adjusted for inflation using the consumer price index (CPI) obtained from GaStat (2021). There are three elements influencing our aggregate real energy price index: Changes in energy prices, inflation, and changes in the shares of the sectors. Using a single aggregate real energy price variable such as this index helps reduce dimensionality issues that arise from including too many separate energy prices as independent variables in an econometric equation.

Figure 2. Aggregate energy price, Saudi Arabian Riyals per tonne of oil equivalent.



Source: Hasanov et al. (2020), GaStat (2021), and authors' calculation

The sectoral value-added manufacturing, services, and agriculture variables were constructed from the data comprising nine aggregated sectors of the Saudi economy obtained from GaStat (2021), which were combined into the three aggregated non-oil sectors to reduce dimensionality. Table 1 displays the sectoral aggregation, and the three aggregated variables are illustrated in Figure 3. Finally, the share of services in non-oil GDP illustrated in Figure 4 was calculated by dividing the value added of total services (as defined in Table 1) by non-oil GDP, both taken from GaStat (2021).

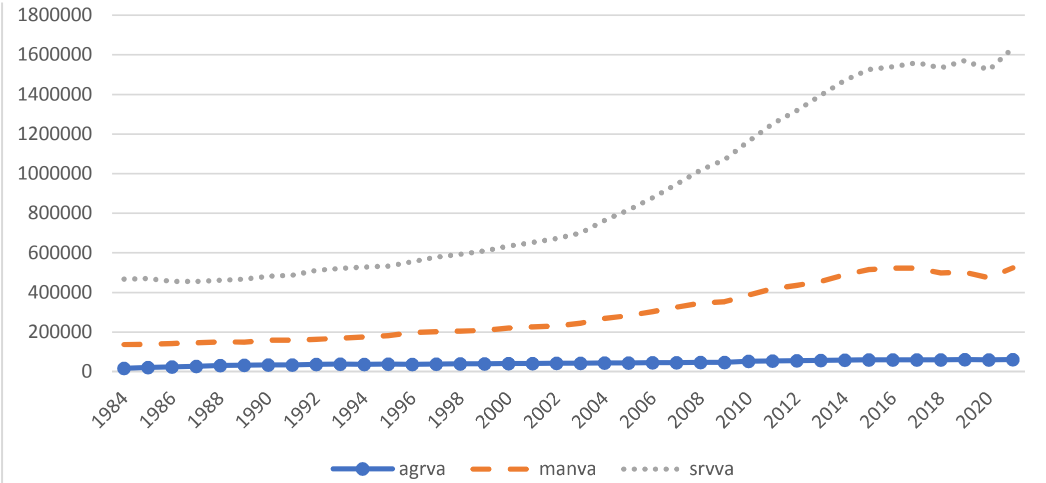
Table 1: Economic Sector Cluster

Economic Sector Breakdown	Sector Aggregation
Agriculture, Forestry & Fishing	Agriculture
Mining & Quarrying	Oil & Gas
Manufacturing	Manufacturing
Electricity, Gas and Water	Manufacturing
Construction	Manufacturing
Wholesale & Retail Trade, Restaurants & hotels	Services
Transport, Storage & Communication	Services
Finance, Insurance, Real Estate & Business Services	Services
Community, Social & Personal Services	Services

Source: GaStat (2021)

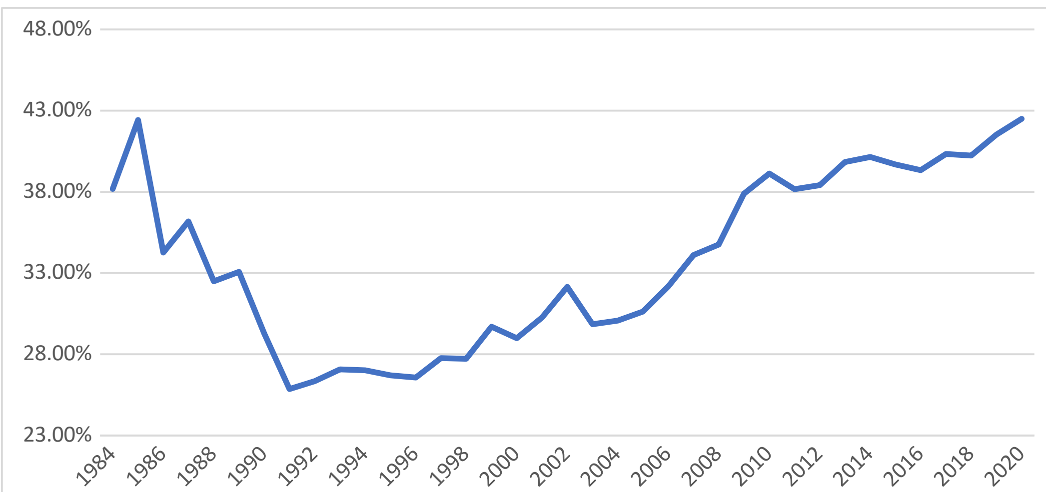
The overarching aim of the estimation is to find a sound, statistically acceptable model that includes appropriate right-hand variables (or drivers) that are important in driving Saudi CO_2

Figure 3. Sectoral value-added numbers (Excluding the Oil Sector), million 2010 Saudi Arabia Riyals, 2010=100.



Source: Gross Domestic Product at Constant Prices, GaStat (2021)

Figure 4. Share of services in non-oil GDP, %.



Source: Authors' calculation based on GaStat (2021)

emissions now and in the future. Therefore, we considered several 'sets' of drivers, $\boldsymbol{X}_t$, in our initial general models that could produce a preferred specification that allows us to develop relevant scenarios. These sets included the following.

- **SET I**: The natural logarithms of gross domestic product (gdp_t) and the real energy price (p_t).
- **SET II**: The natural logarithms of sectoral value added for manufacturing, services, and agriculture ($manva_t$, $agrva_t$, and $srvva_t$) and the real energy price (p_t).
- **SET III**: The natural logarithm of GDP (gdp_t) and the natural logarithm of the real energy price (p_t), and the level share of services in non-oil GDP (SRV_SH_t).

- **SET IV**: The natural logarithms of GDP (gdp_t) the real energy price(p_t), and the share of services in non-oil GDP (srv_sh_t).

The general-to-specific approach described previously was applied to the general model of each of the above sets. SET I was initially considered since GDP and the real energy price were seen as two of the most substantive drivers, and although they prove to be important statistically, the level of economic activity and the structure of the economy are also important in driving CO_2 emissions. Therefore, in SET II, the GDP variable was replaced in the initial general model by the value added of the manufacturing, agriculture, and service sectors. Whereas SET III nests SET I and controls for the share of the value added of services in non-oil GDP. Similarly, SET IV nests SET I but controls for the logarithm of the share of the value added of services in non-oil GDP. Therefore, via the testing down model selection process, the preferred models for SET III and IV could be consistent with SET I (as is the case with the Autometrics estimation). However, none of the final models in SET II, SET III, and SET IV nest each other. The search process for the final models detailed below utilized the general models in SET II, SET III, and SET IV and chose the final model based on congruency in Autometrics and information criteria in the STSM approach and ensuring that, in the selection process, an array of diagnostic tests are satisfied. Table 2 reports the summary statistics of the variables used for the estimation, where upper case letters represent level variables and lower case letters represent variables in logarithms.

Table 2: Summary statistics of variables included in model estimation

VARIABLES	N	mean	sd	min	max
co_2	36	5.671	0.468	4.897	6.357
gdp	36	14.250	0.358	13.565	14.787
p	36	6.509	0.339	5.802	7.117
agrva	36	10.638	0.298	9.784	11.022
manva	36	12.272	0.499	11.674	13.046
srvva	36	13.147	0.448	12.644	13.883
SRV_SH	36	0.666	0.0143	0.643	0.706
srv_sh	36	–0.406	0.021	–0.442	–0.349

Source: Authors' Calculations based on data from GaStat (2021) and Enerdata (2022)

3.2 Scenario Design

We build multiple scenarios to consider the alternate pathways CO_2 emissions in Saudi Arabia might follow over the coming decades. This section introduces the construction and rationale regarding the assumptions pertaining to the underlying drivers, which include GDP growth, the composition of GDP (i.e., the structure of the economy), energy prices, and other exogenous factors, which drive the CO_2 emissions projections up to 2060. For each underlying driver, we construct low, central, and high projection scenarios.

The Saudi GDP projections are initially obtained from the Oxford Economics Model (OEM, 2022), which predicts that the Saudi economy's real growth will average 1.2% per year up to 2060. This would see the Saudi economy grow by 63% by 2060. The OEM's real GDP annual growth rate projection is designated as our low GDP scenario, given that its predicted average growth rate is significantly lower than the historical average growth rate in Saudi Arabia over the last decade. For our central GDP scenario, we increase the OEM GDP annual growth rate projection by a modest 1% to allow for a growth rate that more closely reflects the historical growth rate of the Saudi economy. Since this central GDP scenario reflects the historical data more closely, we set it as our baseline GDP projection. Under this scenario, the economy would double in size by 2060. Finally, for our high GDP scenario, we increase the GDP annual growth rate projection by another 1% over the baseline to construct an optimistic economic growth scenario, which would triple the Saudi economy's size by 2060.

Our low energy price scenario assumes that energy prices remain fixed nominally and thus decline in real terms up to 2060. We set this as our baseline scenario as it extends the historical trend of fixed nominal energy prices since 2018. In our central energy price scenario, we assume that energy prices remain fixed in real terms up to 2060. This central scenario would see nominal energy prices grow 2% per annum during the 2023–2060 period. Finally, our high energy price scenario reflects a wave of energy price reform in 2023, in which nominal energy prices increase significantly, followed by gradual increases in nominal energy prices up to 2030 (at 5% per year). This scenario is picking up a recent announcement of future price changes in Saudi Arabia (Arab News, 2022). This announcement stated that by the fourth quarter of 2023, the government would implement price adjustments to natural gas, Arab heavy crude oil, ethane, heavy fuel oil, and Arab light crude oil. In addition, the government would review those prices annually up to 2030. From 2030 onwards, in our high energy price scenario, we assume that energy prices remain fixed in real terms up to 2060, keeping in line with inflation.

The structure or composition of the Saudi economy is another key driver of CO_2 emissions and was mentioned explicitly in Saudi Arabia's NDC. As noted previously, Saudi Arabia's NDC described two dynamic baselines, one that reflects heavy industrialization and another that reflects economic diversification and a transition towards services. We design our low, central, and high scenarios from the perspective of the share of services. Our central services scenario assumes that the service sector will gradually grow to 62% of the Saudi economy by 2060, with manufacturing accounting for 22% by 2060. This is designated as the baseline scenario as it extends the observed historical trends in the composition of the Saudi economy (GaStat, 2021). Our low service share scenario, or heavy industrialization scenario, sees the share of services grow slowly to 49% by 2060, while the share of manufacturing grows rapidly to 40% by 2060. In our high service share scenario, the service share grows to 75% of the Saudi economy by 2060, in line with several developed economies, while manufacturing declines to 14% by 2060 (Herrendorf et al., 2013).

Lastly, we design different scenarios of how exogenous factors might affect CO_2 emissions moving forward. As discussed previously, the UET captures the combined effect of exogenous factors on CO_2 emissions. These exogenous factors include changes in environmental regulations, increased environmental awareness, cultural changes, changes in tastes and behavior, and improvements in energy efficiency, to name a few. Our central baseline projections extend the UET into the future based on its last observed slope value (this is the default approach used in STSM forecasting.) In our central UET scenario, the trend causes a negligible increase in CO_2 emissions up to 2060. Since UET represents the impact of various exogenous factors, it is hard to make concrete assumptions about all these factors. Hence, to compare with the benchmark baseline, where we assumed the UET to follow the same slope as in the last sample value, we assume a slight change (0.00015 increase or decrease) in the slope of the UET for the alternative scenarios. Under the ceteris paribus condition, a 0.00015 increase (decrease) in the slope of the UET corresponds to the 0.015% increase (decrease) in CO2 emissions driven by factors other than those explicitly entering the model. Our high UET scenario, an unlikely scenario, assumes a change in these exogenous factors that makes the UET more upward-sloping. We construct this high UET scenario by increasing the slope component of the UET by 0.00015 annually. In contrast, our low UET scenario assumes changes in the exogenous factors, such as rapid improvements in energy efficiency, that would make the UET more downward-sloping and, therefore, emission-decreasing. We construct this low UET scenario by decreasing the slope component of the UET by 0.00015 per year. The UET impact on CO_2 emissions is a compelling reminder for policymakers that there are other factors, beyond conventional economic drivers, that can have a significant impact on CO_2 emissions.

4. RESULTS

Estimation results from the Autometrics are presented in sub-section 4.1.1, and from STSM in 4.1.2. Sub-section 4.1.3 discusses the preferred model for the projections. The results of the projections are presented in section 4.2; 4.2.1 discusses the baseline projections, while 4.2.2 details the projections from other scenarios.

4.1.1 Autometrics Specifications

Table 3 gives the estimated preferred specifications from applying the Autometrics estimation strategy outlined above to SET I and SET II only given that no acceptable specification was found for SET III and SET IV; the service share variables were always insignificant and/or the wrong sign. Hence, consistent with the general to specific modeling approach, the estimations that started with SET III and SET IV resulted in the final model for SET I presented in Table 3, which passes all diagnostic tests and includes a few interventions with no lagged dependent variable and only contemporaneous terms for the real energy price and GDP. Furthermore, it suggests that a 1% increase in the real energy price and GDP would reduce CO_2 emissions by 0.14% and increase CO_2 emissions by 0.13%, respectively.

For SET II the final equation includes more interventions than for SET I and passes all diagnostic tests other than the normality test of the residuals that fails at the 10% level of significance. The final equation for SET II, unlike for SET I, does include a lagged dependent variable as well as a contemporaneous term for the real energy price and a contemporaneous and lagged term for manufacturing sector value added. However, the value added for the other sectors were not retained since they were not statistically significant. Therefore, the Autometrics estimated equation for SET II suggests that in the long-run a 1% increase in the real energy price and manufacturing value added would reduce CO_2 emissions by 0.08% and increase CO_2 emissions by 0.81%, respectively.

4.1.2 STSM Specifications

The estimated preferred specifications from applying the STSM procedure to all four sets of explanatory variables are presented in Table 4. For SET I, the final equation includes several interventions and passes all diagnostic tests. There is no lagged dependent variable and, like the Autometrics preferred model for SET I, retains only contemporaneous terms for the real energy price and GDP. The estimated price and income coefficients suggest that a 1% increase in both variables would reduce CO_2 emissions by 0.10% and increase CO_2 emissions by 0.23%, respectively—a similar price response to the Autometrics model for SET I but a somewhat higher GDP response. The preferred model also includes a UET illustrated in the top left-hand side of Figure 5. This UET is generally upward sloping (CO_2 emission increasing), although the rate of increase falls towards the end of the estimation period given the inclusion of a slope intervention in 2015. At the end of the estimation period, holding the real energy price and GDP constant, the trend suggests an autonomous increase in CO_2 emissions of 0.72% per annum—which comes from an estimated underlying slope increase of 4.45% per annum but the slope intervention in 2015 brings this down by 3.73% per annum.

Table 3: Summary of Autometrics Estimation Results (Dependent Variable: CO_{2_t})

	SET I	SET II	SET III	SET IV
Variable / Coefficients				
$Intercept$	5.333***	-2.2140***		
$co_{2_{t-1}}$	-	0.4052***		
p_t	-0.1366***	-0.0483***		
p_{t-1}	-	-		
gdp_t	0.1306**			
gdp_{t-1}	-			
$manva_t$		0.7342***		
$manva_{t-1}$		-0.2504***		
$agrva_t$		-		
$agrva_{t-1}$		-		
$srvva_t$		-		
$srvva_{t-1}$		-		
SRV_SH_t				
SRV_SH_{t-1}				
srv_sh_t				
srv_sh_{t-1}				
Interventions / Indicator	S1:1986** T1:1992*** T1:1993*** T1:2015***	T1:1987*** S1:1990*** S1:1993*** T1:1996*** T11997*** I:2002***	Given the signs of the extra drivers included in the model were not statistically acceptable and/or of the wrong expected sign there is no Autometrics model for SET III	Given the signs of the extra drivers included in the model were not statistically acceptable and/or of the wrong expected sign there is no Autometrics model for SET IV.
Long-run	$\widehat{co_2} = 5.33 - 0.14p + 0.13gdp$	$\widehat{co_2} = -3.72 - 0.08p + 0.81manva$		
Goodness of Fit				
R^2	0.999	0.999		
$\bar{R}^2$	0.999	0.999		
AIC	-5.2345	-5.6781		
SC	-4.9235	-5.1893		
F	$F_{(6, 28)} = 4512$	$F_{(10, 24)} = 4547$		
Residual Diagnostics				
AR(1-2)	$F_{(2, 26)} = 0.02$	$F_{(6, 22)} = 0.02$		
ARCH (1-1)	$F_{(1, 33)} = 0.76$	$F_{(1, 33)} = 0.10$		
Normality	0.87	5.75*		
Hetero	$F_{(10, 24)} = 0.90$	$F_{(15, 18)} = 0.52$		
Hetero-X	$F_{(17, 17)} = 0.69$	n/a		
RESET23	$F_{(2, 26)} = 0.01$	$F_{(2, 22)} = 0.40$		

Notes:
-The blacked-out cells indicate that these variables were not included in the general model before testing down.
- *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively;
- R^2 is the Coefficient of Determination, $\bar{R}^2$ is the Adjusted Coefficient of Determination, F is the overall goodness-of-fit statistic distributed as $F_{(v1, v2)}$, and the *AIC* and *SC* are the Akaike and Schwarz Information Criteria when the log-likelihood constant is included;
- *AR(1-2)* is the 2nd order autocorrelation statistic distributed as $F_{(v1, v2)}$;
- *ARCH (1-1)* is the 1st order autoregressive conditional heteroskedasticity statistic distributed as $F_{(v1, v2)}$;
- Normality is the Doornik and Hansen statistic and is approximately distributed as $\chi^2_{(2)}$;
- Hetero and Hetero-x are heteroscedastic statistics both distributed as $F_{(v1, v2)}$; and
- *RESET* is the Ramsey RESET statistic distributed as $F_{(v1, v2)}$.

For SET II, the final equation includes only one level intervention for 1991 and passes all diagnostic tests. Unlike the preferred Autometrics model for SET II, there is no lagged dependent variable, nor a lagged manufacturing value-added term. However, a contemporaneous term for agriculture value added is retained as is the contemporaneous term for the real energy price (like the Autometrics model). The model, therefore, suggests that a 1% increase in the real energy price would

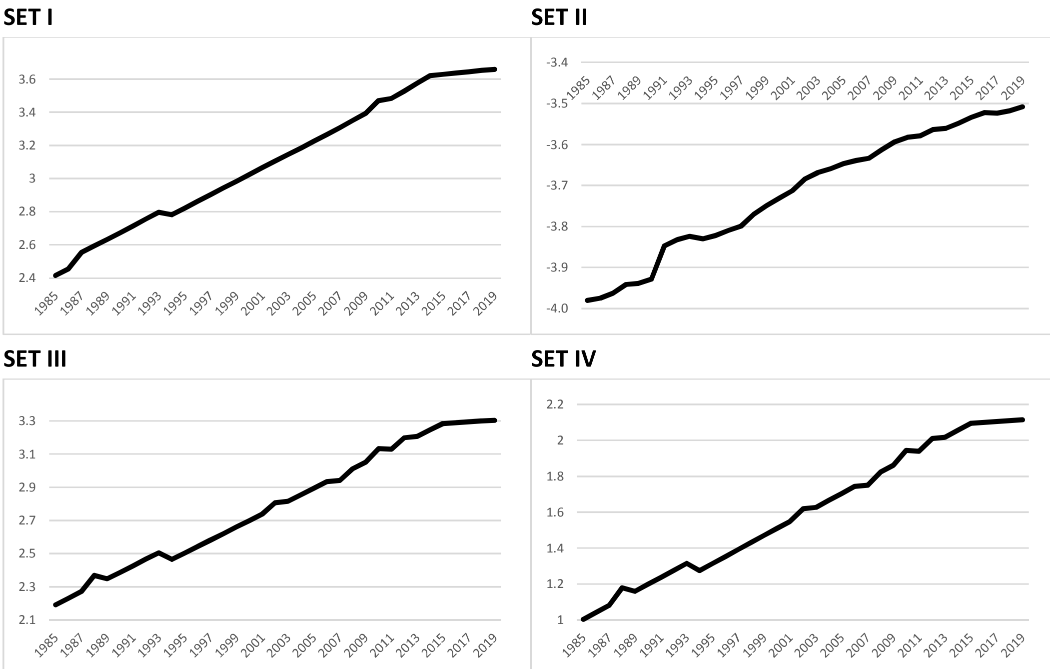
Table 4: Summary of the STSM Estimation Results (Dependent Variable: CO_{2_t})

	SET I	SET II	SET III	SET IV
Variable / Coefficients				
$co_{2_{t-1}}$	-	-	-	-
p_t	-0.1037***	-0.1054***	-0.1174***	-0.1174***
p_{t-1}	-	-	-	-
gdp_t	0.2285***		0.1694***	0.1712***
gdp_{t-1}	-		0.1461***	0.1458***
$manva_t$		0.3986***		
$manva_{t-1}$		-		
$agrva_t$		0.4874***		
$agrva_{t-1}$		-		
$srvva_t$		-		
$srvva_{t-1}$		-		
SRV_SH_t			-1.2455***	
SRV_SH_{t-1}			-	
srv_sh_t				-0.8313***
srv_sh_{t-1}				-
Interventions:	Lvl1987*** Lvl1994*** Irr2010* Slp2015***	Lvl1991***	Irr1988*** Lvl1994*** Irr2002** Irr2007*** Irr2010*** Irr2012** Slp2016***	Irr1988*** Lvl1994*** Irr2002** Irr2007*** Irr2010*** Irr2012** Slp2016***
UET component	Fixed Level Stochastic Slope	Stochastic Level Fixed Slope	Fixed. Level Fixed Slope	Fixed. Level Fixed Slope
Long-run	$\widehat{co_2} = \gamma - 0.10p + 0.23gdp$	$\widehat{co_2} = \gamma - 0.11p + 0.40manva + 0.49agrva$	$\widehat{co_2} = \gamma - 0.12p + 0.32gdp - 1.25SRVSH\_NO$	$\widehat{co_2} = \gamma - 0.12p + 0.32gdp - 0.83srvsh\_no$
Goodness of Fit				
p.e.v.	0.00031018	0.00035536	0.00007197	0.00007255
AIC	-7.5641	-7.5424	-8.7393	-8.7313
BIC	-7.1641	-7.2313	-8.1172	-8.1092
R^2	0.9988	0.9986	0.9998	0.9998
R_d^2	0.8206	0.7793	0.9661	0.9658
Residual Diagnostics				
Normality	0.84	0.08	0.04	0.03
$H_{(n)}$	$H_{(9)}$ = 1.65	$H_{(9)}$ = 0.73	$H_{(7)}$ = 0.82	$H_{(7)}$ = 0.80
$r_{(1)}$	-0.08	-0.03	0.01	0.01
$r_{(2)}$	-0.16	-0.07	-0.00	-0.00
$r_{(3)}$	-0.10	0.08	-0.00	-0.00
$r_{(q)}$	$r_{(6)}$ = 0.02	$r_{(6)}$ = 0.20	$r_{(5)}$ = -0.12	$r_{(5)}$ = -0.12
$Q_{(q,q\text{-}p)}$	$\chi^2_{(4)}$ = 2.87	$\chi^2_{(4)}$ = 5.76	$\chi^2_{(3)}$ = 0.76	$\chi^2_{(3)}$ = 0.80
Auxiliary Residuals				
Normality–Irregular	0.36	0.74	0.69	0.70
Normality – Level	1.23	0.16	1.43	1.28
Normality – Slope	4.13	2.42	0.56	0.64
Prediction Failure	$\chi^2_{(7)}$= 11.30	$\chi^2_{(8)}$= 6.58	$\chi^2_{(6)}$= 3.76	$\chi^2_{(6)}$= 3.71

Notes:
-The blacked-out cells indicate that these variables were not included in the general model before testing down.
- *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively;
- R^2 is the Coefficient of Determination, R_d^2 is the Coefficient of Determination based on differences, and the p.e.v. is the Prediction Error Variance (p.e.v.);
- *AIC* and *BIC* are Akaike and Bayesian Information Criteria based on p.e.v.
- Normality are the Bowman—Shenton statistics and are approximately distributed as $\chi^2_{(2)}$;
- *H(n)* is a Heteroscedasticity statistic distributed as $F_{(n,n)}$;
- *r(1)*, *r(2)*, *r(3)*, and *r(q)* are the serial correlation coefficients at the equivalent residual lags, approximately normally distributed;
- *Q(q,q-p)* is the Box—Ljung statistic distributed as $\chi^2_{(q-p)}$; and
- Prediction Failure is a predictive failure statistic distributed as $\chi^2_{(f)}$.

reduce CO_2 emissions by 0.11% and a 1% increase in manufacturing value added and agriculture value added would increase CO_2 emissions by 0.40% and 0.49%, respectively—somewhat different to that obtained by the Autometrics estimates for SET II. The estimated UET for the STSM equation for SET II is illustrated in the top right-hand side of Figure 5 and again is generally upward sloping and at the end of the estimation period, holding the real energy price, manufacturing value added, and agriculture value added constant, the trend suggests an autonomous increase in CO_2 emissions of 1.19% per annum—somewhat larger than that for the SET I STSM specification.

Figure 5: Estimated Underlying Emissions Trends (UETs) for the STSM preferred specifications.



The preferred specifications for SET III and SET IV are very similar with the same interventions, the same terms retained for the real energy price and GDP; the only difference being that in SET III the contemporaneous term for the share of services value added in non-oil GDP is included whereas for SET IV it is the natural logarithm of the share of services value added in non-oil GDP instead. Furthermore, both pass all diagnostic tests, and both suggest that a 1% increase in the real energy price and GDP would reduce CO_2 emissions by 0.12% and increase CO_2 emissions by 0.32%, respectively. Not surprisingly, the estimated UETs for the two specifications are also very similar, as illustrated in the bottom half of Figure 5. Moreover, both trends suggest that, at the end of the estimation period, holding the set of drivers constant, there would be an autonomous increase in CO_2 emissions of 0.45% per annum made up of an estimated underlying slope increase of 3.91% per annum that is reduced somewhat by the break in the slope in 2016 (i.e., the estimated slope intervention in 2016) to 3.46% per annum; thus, the only difference between the SET III and SET IV estimated models is the way services value added is entered in the equations. For SET III it is the actual proportionate share of services in non-oil GDP and the estimated coefficient suggests that a one percentage point increase in the share would reduce CO_2 emissions by 1.25% whereas for SET

IV it is the natural logarithm of the share and the estimated coefficient suggests that a one percentage increase in the share would reduce CO_2 emissions by 0.83%.

4.1.3 Preferred Specification for Baseline Prediction and Scenarios

The previous section presented several results using the two different methodologies and the different sets of explanatory variables. This illustrates our attempt to find a sound statistically acceptable model that includes the appropriate and important drivers that affect CO_2 emissions now and in the future. Multiple assumptions on the evolution of these underlying drivers are used to underpin the CO_2 emissions scenarios. Therefore, a choice had to be made from those models presented above based on their statistical validity and the usefulness of the models for the scenario policy analysis.

When considering the two Autometrics specifications in Table 3, the specification for SET II has the lower information criteria but fails one of the diagnostic tests—given this, and that no preferred specification was found for SET III nor SET IV, on balance the SET I specification that includes the real energy price and GDP is preferred. When considering the four STSM specifications in Table 4, they all pass all the diagnostic tests, but the specifications for SET III and SET IV clearly have lower information criteria than the specifications for SET I and SET II—so this would suggest the choice is between the SET III and SET IV specifications. Out of these two, it is a close decision, but given that the SET III specification has slightly lower information criteria and that the interpretation of the level share rather than the natural log of the share is easier, it is preferred to the SET IV specification. Thus, it comes down to choosing between the Autometrics specification for SET I and the STSM specification for SET III. To aid the choice, we conducted a range of encompassing tests detailed in the Appendix, which clearly suggest that the SET III STSM specification dominates the SET I Autometrics specification. Furthermore, the SET III STSM specification has the advantage of including extra drivers compared to the SET I Autometrics specification in terms of the service value added share and the trend. Therefore, the SET III STSM specification was used to generate the scenarios detailed in the following sections. In summary, this specification is given by:

$$\widehat{CO_{2_t}} = \hat{\gamma}_t + 0.1694^{***} gdp_t + 01461^{***} gdp_{t-1} - 0.1174^{***} p_t - 1.2455^{***} SRV\_SH_t \qquad (3a)$$

with the estimated Underlying Emissions Trend (UET) (the SETT III , shown in Figure 6) given by:

$$\begin{aligned}\hat{\gamma}_t = \hat{\mu}_t &- 0.0594^{***} Irr_{1988} - 0.0798^{***} Lvl_{1994} + 0.0307^{**} Irr_{2002} - 0.0327^{***} Irr_{2007} \\ &+ 0.0435^{***} Irr_{2010} + 0.0309^{**} Irr_{2012} - 0.0346^{***} Slp_{2016} \qquad (3b)\end{aligned}$$

Where, Irr_t represents an irregular (or outlier) intervention, Lvl_t represents a level intervention, and Slp_t represents a slope intervention, all at time t; *, **, and *** represent coefficients significant at the 10%, 5%, and 1% levels, respectively; and $\hat{\mu}_t$ represents the estimated level component of the trend.

The preferred STSM specification suggests that in the long-run, a one percent increase in GDP would increase CO_2 emissions by 0.32%. A one percent increase in the real energy price would reduce CO_2 emissions by 0.12%, and a one percentage point increase in the share of services value added in non-oil GDP would reduce CO_2 emissions by 1.25%. Furthermore, the estimated UET, at the end of the estimation period (and therefore for the baseline projection) suggests that holding GDP, the real energy price, and the share of services value added in non-oil GDP constant, there would be an autonomous increase in CO2 emissions of 0.45% per annum—which comes from an estimated underlying slope increase of 3.91% per annum but tempered by the break in the slope in 2016 (i.e., the estimated slope intervention in 2016) of 3.46% per annum. It is worth noting that the

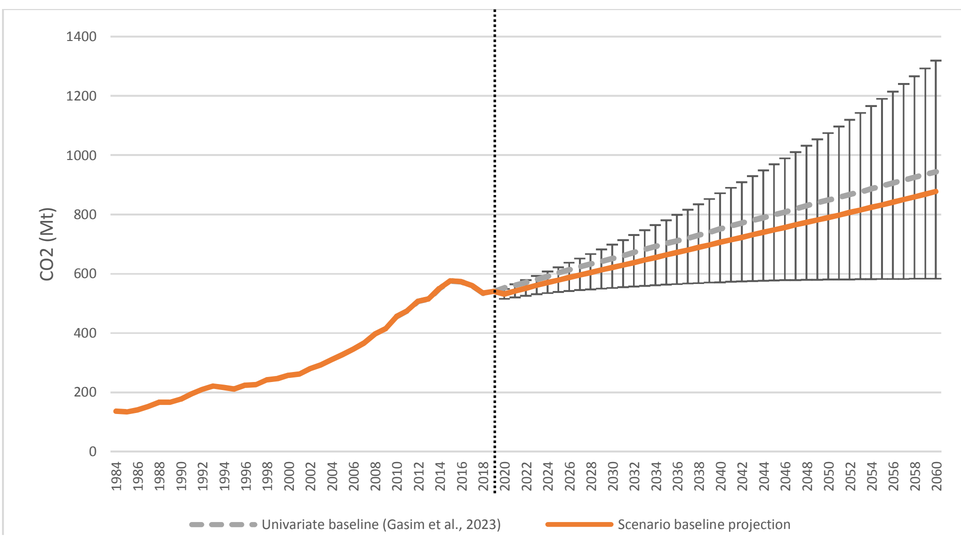
UET captures the combined effect of exogenous factors on CO_2 emissions. These exogenous factors include changes in environmental regulations, increased environmental awareness, cultural changes, changes in tastes and behavior, and improvements in energy efficiency, to name a few. The literature finds evidence that developing countries historically have an upward-sloping trend. For example, Javid and Khan (2020) find an increasing slope of the emission trend in China and India and suggest that their energy-saving behavior (80–90%) of emissions has not been utilized. The trend is also historically upward for Saudi Arabia concerning the underlying energy demand trend; see (Aldubyan & Gasim, 2021) for further details.

4.2 Scenario Projections

4.2.1 Baseline Projection

Before considering the other scenarios, we present our baseline scenario projection, which acts as a reference, showing how CO_2 emissions might evolve without any additional policy efforts, assuming the underlying drivers continue to evolve in the future as they did in the past. Our baseline scenario rests on assumptions about how GDP, energy prices, the share of services, and other exogenous factors captured by the UET would evolve until 2060. Our baseline scenario assumptions, described previously, extend past historical trends into the future. By plugging these assumptions into our preferred econometric equation, we generate our baseline scenario, which is presented in Figure 6. Our baseline scenario projection suggests that Saudi CO_2 emissions would rise from 540 Mt in 2019 to 621 Mt in 2030 and 878 Mt in 2060. Also included in Figure 6, as a benchmark, is a previous baseline projection based on a univariate modeling approach from Gasim et al. (2022). Our baseline projection in this paper is not dissimilar to the Gasim et al. (2023) projection and is within the statistical confidence interval of their baseline projection shown in Figure 6.

Figure 6. CO_2 Baseline Projection



Source: Gasim et al. (2023).

Table 5. Scenario results of CO_2 Projections

<table>
<tr><th>Scenario</th><th>GDP real average growth 2020-2060:</th><th>Energy prices:</th><th>Services share by 2060:</th><th>Underlying Emission Trend:</th><th>CO₂ Emission 2030</th><th>CO₂ Emission 2060</th></tr>
<tr><td>Baseline</td><td>2.2%
(central)</td><td rowspan="3">Fixed in nominal terms
(low)</td><td rowspan="5">62%
(central)</td><td rowspan="7">Last observed slope
(central)</td><td>621 Mt</td><td>878 Mt</td></tr>
<tr><td>High GDP</td><td>3.1 %
(high)</td><td>635 Mt</td><td>985 Mt</td></tr>
<tr><td>Low GDP</td><td>1.2 %
(low)</td><td>607 Mt</td><td>781 Mt</td></tr>
<tr><td>High energy prices</td><td rowspan="6">2.2%
(central)</td><td>Increasing up to 2030 then fixed in real terms
(high)</td><td>548 Mt</td><td>674 Mt</td></tr>
<tr><td>Central energy prices</td><td>Fixed in real terms
(low)</td><td>611 Mt</td><td>805 Mt</td></tr>
<tr><td>Low Service</td><td rowspan="4">Fixed Nominally
(low)</td><td>49%
(low)</td><td>646 Mt</td><td>1,096 Mt</td></tr>
<tr><td>High Service</td><td>75%
(high)</td><td>602 Mt</td><td>769 Mt</td></tr>
<tr><td>Low UET</td><td rowspan="2">62%
(central)</td><td>Exogenous Non-economic factors improving</td><td>616 Mt</td><td>776 Mt</td></tr>
<tr><td>High UET</td><td>Exogenous Non-economic factors declining</td><td>626 Mt</td><td>992 Mt</td></tr>
<tr><td>Lowest emissions</td><td>1.2 %
(low)</td><td>Increasing up to 2030 then fixed in real terms
(high)</td><td>75% (high)</td><td>Slope declining annually below last observed value (low)</td><td>516 Mt</td><td>465 Mt</td></tr>
<tr><td>Highest emissions</td><td>3.1 %
(high)</td><td>Fixed in nominal terms
(low)</td><td>49%
(low)</td><td>Slope increasing annually above last observed value (high)</td><td>666 Mt</td><td>1,391 Mt</td></tr>
</table>

4.2.2 Scenario Projections

In addition to the baseline, we demonstrate the impacts of economic growth trajectories, economic diversification, energy price fluctuations, and energy efficiency, among other determinants, on prospective CO_2 emissions in Saudi Arabia. Table 5 outlines our diverse assumptions regarding these underlying drivers, highlighting the CO_2 emissions projections derived from each scenario by plugging these assumptions into the preferred econometric equation. As previously mentioned, our baseline scenario projects CO_2 emissions of 621 Mt in 2030 and 878 Mt in 2060.

Increasing the GDP growth rates while maintaining all other underlying drivers at their baseline values results in a CO_2 emissions projection reaching 635 Mt by 2030 in the high GDP scenario. Conversely, a reduction in GDP growth rates yields a projection of only 607 Mt by 2030. Although the disparity between the low and high GDP scenarios is relatively modest in 2030 (28 Mt), it expands to 204 Mt by 2060, the year of Saudi Arabia's net-zero ambition.

Raising energy prices above their low scenario, designated as the baseline, yields scenarios with reduced CO_2 emissions. Assuming constant energy prices in real terms (central energy prices scenario), CO_2 emissions are projected to reach 611 Mt by 2030, approximately 10 Mt below the baseline scenario value. Under the high energy prices scenario, implementing energy price reforms leads to CO_2 emissions in 2030 growing to 548 Mt, nearly 70 Mt lower than the baseline, emphasizing the substantial potential impact of energy price reform, even in the near term. In the long term, the gap between the high and low energy prices scenarios (i.e., the baseline) widens to 204 Mt.

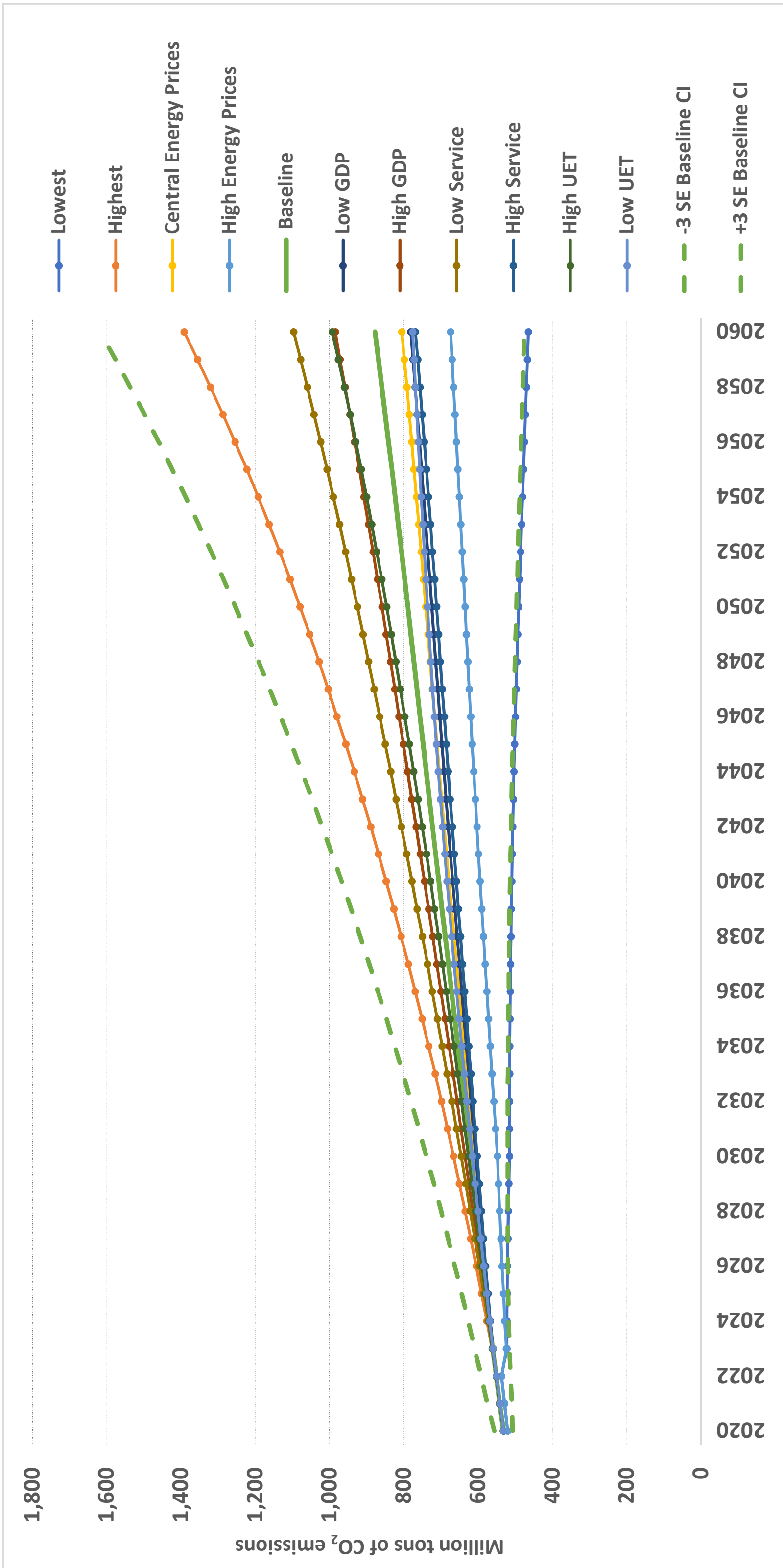
As reflected in the share of services, the GDP composition significantly influences CO_2 emissions. Under the low services scenario, manufacturing expands rapidly to 40% by 2060, while the services sector experiences slow growth, reaching only 49%, resulting in CO_2 emissions of 646 Mt in 2030 and 1,096 Mt in 2060. This low services scenario aligns with the heavy industrialization scenario in Saudi Arabia's NDC. Conversely, if the services sector grows to 75% of GDP by 2060, emissions would be 602 Mt (46 Mt less than the heavy industrialization scenario) in 2030 and 769 Mt in 2060 (327 Mt less than the heavy industrialization scenario). This high services scenario aligns with the economic diversification scenario in Saudi Arabia's NDC. In summary, our findings underscore the impact of GDP composition on CO_2 emission projections, revealing the rationale behind the Saudi government's emphasis on this factor in its updated NDC.

The UET, encompassing the combined impact of multiple exogenous factors, was manipulated to reveal how these factors could influence CO_2 emission projections. In the low UET scenario (a more downward-sloping EUT), which may encapsulate accelerated improvements in energy efficiency and changes in behavior reducing emissions, CO_2 emissions grow to 616 Mt in 2030 and 776 Mt in 2060. In the high UET scenario (a more upward-sloping EUT), CO_2 emissions grow to 626 Mt in 2030 and 992 Mt in 2060. Our findings suggest that, beyond the economic factors considered previously, other factors could significantly influence the evolution of CO_2 emissions in Saudi Arabia.

Finally, we introduce the "highest" and "lowest" emission scenarios, reflecting the combination of assumptions on each underlying driver yielding the highest and lowest CO_2 emissions projections. Under the highest scenario, GDP grows fastest, and the economy becomes more heavily industrialized, energy prices decline in real terms, and the UET upward-sloping. With this combination of assumptions, CO_2 emissions would grow to 666 Mt in 2030 and 1,391 Mt by 2060. Conversely, under our lowest scenario, GDP grows at its slowest, energy prices are reformed, the economy diversifies towards services, and the UET becomes more downward-sloping. With this combination of assumptions, CO_2 emissions would decline to 516 Mt in 2030 and 465 Mt by 2060.

Figure 7 overlays all these scenarios into one chart, illustrating the various CO_2 emissions pathways for Saudi Arabia. These scenarios highlight how different factors affect CO_2 emissions

Figure 7: Fan chart of CO_2 emission projections for Saudi Arabia (all scenarios)



Note: 3 SE CI stands for three standard deviation error (SE) bands for the baseline scenario, which represents the 99% confidence interval (CI).

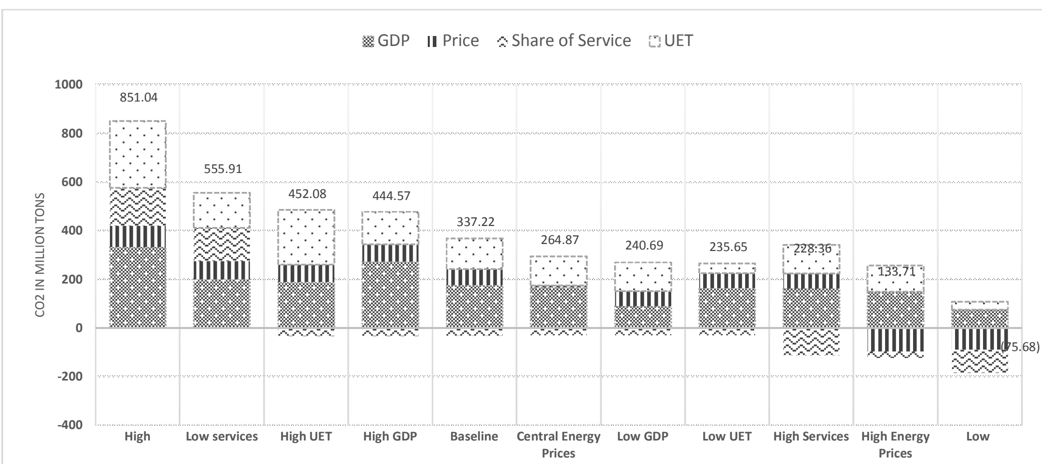
in Saudi Arabia up to 2060. The gap between the highest and lowest projections underscores how emissions could evolve differently depending on the underlying drivers and the implications of Saudi efforts to reduce emissions. One key policy implication is that the Saudi government will need to implement more comprehensive policies or carbon removal technologies for Saudi Arabia to achieve its net-zero ambition.

Figure 8 also demonstrates the 99% confidence interval for the baseline scenario to give an idea of the uncertainty around the simulated scenarios. All scenarios remain within the interval bands except the lowest scenario at the end of the forecast horizon.

In addition to the fan chart presented in Figure 7, we provide in Figure 8 a decomposition of the economic drivers for all the scenarios, quantifying the contribution of each driver to the net change in CO_2 emission from 2019 to 2060. For example, in our high scenario case, CO_2 increases by 851 Mt from its 2019 levels, and GDP is the highest factor (333.5 Mt) in terms of its contribution, followed by the share of services, which shrinks over time in this scenario. Energy prices remain stagnant, declining in real terms, contributing to a CO_2 increase (86.4 Mt). Furthermore, no improvements in other exogenous factors contribute to increasing CO_2 as well through the UET (274.48 Mt).

In contrast, in the low scenario, CO_2 emissions decline by 76 Mt from its 2019 level to reach 464.7 Mt by 2060. This net negative change includes a positive contribution through GDP growth (74.7 Mt), in addition to a positive contribution through the UET (33 Mt). The net negative change is mainly driven by the negative contribution of higher energy prices (–88 Mt) and the structure of the economy becoming more concentrated in services (–95 Mt). Collectively, these drivers reduce CO_2 emissions by roughly 14% from their 2019 levels.

Figure 8: Decomposition of economic factors impacting CO_2 emissions for all scenarios.



Note: The numerical labels are the net change in CO2 emissions (from 2019 to 2060) resulting from the summation of the effects of changes in all four driver over the decomposition period.

5. CONCLUSION AND POLICY IMPLICATIONS

As a party to the Paris Agreement, Saudi Arabia has recently submitted its updated NDC, announcing its pledge to reduce its GHG emissions by 278 $MtCO_2eq$ annually by 2030 below its baseline (Kingdom of Saudi Arabia, 2021, p. 2). Saudi Arabia's NDC emission target is a baseline target that requires a quantitative baseline scenario showing how emissions would evolve if there were no further policies or actions. Although Saudi Arabia is one of the countries that did not yet publicly announce a quantitative baseline in its NDC, it did provide qualitative details on its "dynamic baselines" (Kingdom of Saudi Arabia, 2021, p. 3). Saudi Arabia's dynamic baselines depend on both the level of economic development and the extent of economic diversification that occurs in the country over the coming years.

To better understand Saudi Arabia's baseline emissions scenario and how factors such as GDP and the structure of the economy influence emissions, we first model Saudi Arabian CO_2 emissions using econometrics and then generate CO_2 emissions projections under different sets of assumptions for the underlying drivers. The underlying drivers we consider include GDP, energy prices, the structure of the economy, and other exogenous factors (represented by the UET).

We model CO_2 emissions by utilizing the general-to-specific approach via Autometrics and the STSM, two econometric methods that allow for greater flexibility in modeling a variable such as CO_2 emissions. We estimate multiple equations that include different right-hand side variables across both methods. Our econometric results reveal that the coefficients on variables such as GDP and energy prices are consistent across the estimated equations, which points to the coefficients' robustness. To generate the CO_2 emissions projections across the different scenarios, we settle on a preferred equation that passes all diagnostic tests and is most useful in terms of the number of policy scenarios it allows us to run.

Before using our preferred econometric model to generate projections, we build scenarios that reflect different assumptions on the underlying drivers of CO_2 emissions. These drivers include GDP, energy prices, and economic structure, along with the UET, which captures the combined effect of exogenous factors such as consumer behavior and energy efficiency. We build 11 scenarios, including a baseline scenario that acts as a reference, showing how CO_2 emissions might evolve in Saudi Arabia without any additional policy efforts and if the underlying drivers continue to evolve in the future as they did in the past. We generate our baseline CO_2 emissions projection inputting the baseline assumptions for the drivers into our preferred econometric model. Our baseline suggests that Saudi CO_2 emissions would rise from 540 Mt in 2019 to 621 Mt in 2030 and 878 Mt in 2060.

Our scenarios highlight how different factors affect CO_2 emissions in Saudi Arabia up to 2060. The gap between the highest and lowest projections underscores how much emissions could evolve differently depending on the underlying drivers. In the highest scenario, in which GDP grows fastest, the economy becomes more heavily industrialized, energy prices decline in real terms, and the UET grows more upward-sloping, CO_2 emissions would grow to 666 Mt in 2030 and 1,391 Mt by 2060. On the other hand, in the lowest scenario, in which GDP grows slowest, energy prices are reformed, the economy diversifies, and the UET becomes more downward-sloping, CO_2 emissions would decline to 516 Mt in 2030 and 465 Mt by 2060.

Besides the highest and lowest scenarios, we highlight how the underlying drivers can separately influence CO_2 emissions. Given the emphasis the Saudi NDC placed on the structure of the economy and economic development, we highlight how both variables separately affect CO_2 emission trajectories. In the case of economic structure, we show that under a low services share scenario, in which manufacturing grows rapidly to contribute 40% to GDP by 2060, while the services sector grows slowly to 49% only, CO_2 emissions would rise to 646 Mt in 2030 and 1,096 Mt in 2060. This low services share scenario is aligned with the heavy industrialization scenario presented in Saudi Arabia's NDC as one of its dynamic baselines. In contrast, under the high services share scenario, in which services grow to contribute 75% of GDP by 2060, CO_2 emissions would grow to 602 Mt in 2030 and 769 Mt in 2060. This high services scenario is aligned with the economic diversification scenario presented in Saudi Arabia's NDC. Both scenarios differ by 46 Mt by 2030 and

327 Mt by 2060, underscoring the impact of the composition of GDP on CO_2 emission projections. Similarly, we show that in a high GDP growth scenario, CO_2 emissions would grow to 635 Mt in 2030 and 985 Mt in 2060, while in a low GDP growth scenario, CO_2 emissions would grow to 607 Mt in 2030 and 781 Mt in 2060. These results reveal why the Saudi government emphasized both variables in its updated NDC.

Although baseline targets in NDCs are useful for developing countries expecting to grow, such targets introduce additional processes and challenges for those countries (Vaidyula & Hood, 2018). Baseline targets require the estimation of a baseline scenario, which is not needed when setting an absolute emissions target relative to a historical base year. Countries setting baseline targets in their NDCs will need to carefully explain the data and method used for estimation and the assumptions to ensure transparency. As we have shown using econometric methods, assumptions around drivers such as GDP and economic structure can substantially affect emission projections, especially in the long term. The impacts of these assumptions are relatively smaller but still significant in the short term (e.g., up to 2030). Countries with baseline targets must also decide which existing or planned policies are included or excluded from their baseline. For example, some of our baselines included future energy price reforms, while others did not, with considerable implications on the projections. Countries will also need to account for the uncertainties associated with baseline projections, which we have highlighted in our study. Moreover, as countries update their NDCs, they may need to update their baselines, especially if the drivers evolve differently than initially projected. These updates may involve revisions to critical assumptions like GDP growth but also revisions to key parameters, such as the coefficients we estimated in this paper using econometric methods, which may change over time. Just as it is considered good practice for countries to ensure transparency, accuracy, completeness, comparability, and consistency (TACCC) of their national GHG inventories (IPCC, 2019), countries with baseline targets would ideally want to incorporate these TACCC principles into the development and updating of their NDC baseline scenarios, which can be challenging.

To conclude, our paper generates several key insights for policymakers. It highlights the challenges around estimating baseline emission scenarios and shows how different variables, such as GDP and energy prices, influence CO_2 emissions projections. It also reveals the critical role the economy's structure can play, especially in countries like Saudi Arabia undergoing a rapid economic transformation. This paper also demonstrates that even in the lowest emissions scenario, further efforts are needed to achieve net zero by 2060. These efforts could encompass policies such as carbon pricing and investment in carbon removal technologies. These additional efforts will be necessary for the Kingdom of Saudi Arabia to achieve its NDC and net-zero targets.

ACKNOWLEDGMENTS

An earlier version of this paper was presented at the 2023 44th IAEE International Conference, Riyadh, Saudi Arabia, and we are grateful to the participants for their comments and suggestions. We would also like to thank Muhammad Javid, Fateh Belaid, and three anonymous reviewers for their extremely helpful comments that helped to significantly improve the paper. Nevertheless, the views expressed in this paper are those of the authors alone and do not necessarily represent the views of their affiliated institutions and we are, of course, responsible for all errors and omissions. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

REFERENCES

Aldubayan, Mohammad and Anwar Gasim (2021). "Energy price reform in Saudi Arabia: Modeling the economic and environmental impacts and understanding the demand response." *Energy Policy*. https://doi.org/10.1016/j.enpol.2020.111941 .

Alkhathlan, K. and Muhammad Javid (2013). "Energy consumption, carbon emissions and economic growth in Saudi Arabia: An aggregate and disaggregate analysis." *Energy Policy* 62(1): 1525–1532. https://doi.org/10.1016/j.enpol.2013.07.068.

Al-mulali, Usama and Chor Foon Tang (2013). "Investigating the validity of the pollution haven hypothesis in the Gulf Cooperation Council (GCC) countries." *Energy Policy* 60(1): 813–819. https://doi.org/10.1016/j.enpol.2013.05.055.

Alshammari, Yousef M. 2020. "Achieving Climate Targets via the Circular Carbon Economy: The Case of Saudi Arabia." C – *Journal of Carbon Research* 6(3): 54. https://doi.org/10.3390/c6030054.

Arab News (2021). "Saudi Arabia to reach net zero carbon by 2060: Crown Prince Mohammed bin Salman." Available at: https://www.arabnews.com/node/1953441/business-economy .

Brown, Robert L., James Durbin, and James M. Evans (1975). "Techniques for testing the constancy of regression relationships over time." *Journal of the Royal Statistical Society: Series B (Methodological)* 37(2): 149–192. https://doi.org/10.1111/j.2517-6161.1975.tb01532.x.

Castle, Jennifer L., David F. Hendry, and Andrew B. Martinez (2017). "Evaluating forecasts, narratives, and policy using a test of invariance." *Econometrics* 5(39). https://doi.org/10.3390/econometrics5030039 .

Castle, Jennifer L., Jurgen A. Doornik, and David F. Hendry (2021). "Selecting a Model for Forecasting." *Econometrics* 9(3): 26. https://doi.org/10.3390/econometrics9030026.

Cox, D.R. (1961). Tests of separate families of hypotheses, in Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, vol.1, pp.105–123.

Doornik, Jorgen A. and David F. Hendry (2018). *Empirical Econometric Modelling Using PcGive: Volume I,* 8th Edition. London: Timberlake Consultants Press. .

Enders, W. (2015). *Applied Econometrics Time Series*. Hoboken, NJ: Wiley.

Enerdata (2022). Global Energy & CO2 Data. Enerdata, Grenoble, France.

Ericsson, N.R. (1983). "Asymptotic Properties of Instrumental Variables Statistics for Testing Non-Nested Hypotheses." *The Review of Economic Studies* 50(2): 287–304. https://doi.org/10.2307/2297417.

Gasim, Anwar A., Lester C. Hunt, Jeyhun I. Mikayilov (2023). "Carbon dioxide emission baseline forecasts for Saudi Arabia using the Structural Time Series Model and Autometrics." *KAPSARC Discussion Paper.* https://doi.org/10.30573/KS-2022-DP19 .

GaStat, General Authority for Statistics (2021). Accessed on December 4, 2022. https://database.stats.gov.sa/beta/dashboard/indicator/410.

Guven, Denizhan and Özgür Kayakutlu (2020). "CO2 emissions analysis for East European countries: the role of underlying emission trend." *Environmental Economics* 11(1): 67–81. https://doi.org/10.21511/ee.11(1).2020.07.

Harvey, Andrew. C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press, Cambridge, UK. https://doi.org/10.1017/CBO9781107049994.

Harvey, Andrew C. and Siem J. Koopman (1992). "Diagnostic Checking of Unobserved-Components Time Series Models." *Journal of Business and Economic Statistics* 10: 377–389. https://doi.org/10.1080/07350015.1992.10509913.

Hendry, David F., and Carlos Santos (2010). "An automatic test of super exogeneity." In M.W. Watson, T. Bollerslev, and J. Russell (Eds.), *Volatility and time series econometrics* (pp. 164–193). Oxford: Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199549498.003.0009.

Hendry, David F. (2020). "First in, First out: Econometric Modelling of UK Annual CO2 Emissions, 1860–2017." Accessed on March 3, 2022. https://www.nuffield.ox.ac.uk/economics/papers/2020/2020W02_CO2UKEmissionsModel20.pdf .

Hendry, David F. and Doornik A. Jorgen (2014). *Empirical Model Discovery and Theory Evaluation. Automatic Selection Methods in Econometrics.* The MIT Press, Cambridge, Massachusetts. London, England. https://doi.org/10.7551/mitpress/9780262028356.001.0001.

Herrendorf, Berthold, Richard Rogerson and Ákos Valentinyi (2013). "Growth and Structural Transformation." National Bureau of Economic Research. https://doi.org/10.3386/w18996 .

Hunt, Lester C. and Yasushi Ninomiya (2003). "Unravelling trends and seasonality: a structural time series analysis of transport oil demand in the UK and Japan." *The Energy Journal* 24(3): 63–96. https://doi.org/10.5547/ISSN0195-6574-EJ-Vol24-No3-3.

Hunt, Lester C., George Judge, and Yasushi Ninomiya (2003). "Underlying Trends and Seasonality in UK Energy Demand: A Sectoral Analysis." *Energy Economics* 25(1): 93–118. https://doi.org/10.1016/S0140-9883(02)00072-5.

IPCC. (2019). Chapter 1: *Introduction to National GHG Inventories.* 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, IPCC. .

Jaforullah, Mohammad, and Alan King (2017). "The econometric consequences of an energy consumption variable in a model of CO2 emissions." *Energy Economics* 63(1): 84–91. https://doi.org/10.1016/j.eneco.2017.01.025.

Javid, Muhammad and Muhammad Khan (2020). "Energy efficiency and underlying carbon emission trends." *Environmental Science and Pollution Research* 27(3): 3224–3236. https://doi.org/10.1007/s11356-019-07019-4.

Kennedy, Peter (2008). *A Guide to Econometrics*, 6th Edition, ISBN 978-1-4051-8258-4, Blackwell Publishing, 350 Main Street, Malden, MA 02148-5020, USA.

Kingdom of Saudi Arabia (2015). "The Intended Nationally Determined Contribution of the Kingdom of Saudi Arabia under the UNFCCC." Accessed September 25, 2022. Available at: https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx .

Kingdom of Saudi Arabia (2021). Updated First Nationally Determined Contribution." Accessed September 25, 2022. Available at: https://www4.unfccc.int/sites/NDCStaging/Pages/All.aspx .

Köne, Aylem Çiğdem, and Büke Tayfun (2010). "Forecasting of CO2 Emissions from Fuel Combustion Using Trend Analysis." *Renewable and Sustainable Energy Reviews* 14(9): 2906–15. https://doi.org/10.1016/j.rser.2010.06.006.

Koopman, Siem J., Andrew. C. Harvey, Jorgen. A. Doornik, and Neil Shephard (2007). *STAMP: Structural Time Series Analyser, Modeller and Predictor: STAMP 8.* Timberlake Consultants Press, London.

Mahmood, Haider, Alam Asadov, Muhammad Tanveer, Muhammad Furqan, and Zhang Yu (2022). " Impact of Oil Price, Economic Growth, and Urbanization on CO2 Emissions in GCC Countries: Asymmetry Analysis." *Sustainability* 14: 4562. https://doi:10.3390/su14084562 .

Omri, Anis (2013). "CO2 emissions, energy consumption and economic growth nexus in MENA countries: Evidence from simultaneous equations models." *Energy Economics* 40(1): 657–664. https://doi.org/10.1016/j.eneco.2013.09.003.

Omri, Anis, Saida Daly, Christophe Rault, and Anissa Chaibi (2015). "Financial development, environmental quality, trade and economic growth: What causes what in MENA countries." *Energy Economics* 48(2015): 242–252. https://doi.org/10.1016/j.eneco.2015.01.008.

Onifade, Stephen Taiwo, Andrew Adewale Alola, Savaş Erdoğan, and Hakan Acet (2020). "Environmental aspect of energy transition and urbanization in the OPEC member states." *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-020-12181-1 .

Oxford Economics (2022). Oxford Economics. Global Economic Model. Accessed September 25, 2023. https://www.oxfordeconomics.com/service/subscription-services/macro/global-economic-model .

Ozcan, Burcu (2013). "The nexus between carbon emissions, energy consumption, and economic growth in Middle East countries: A panel data analysis." *Energy Policy* 62(1): 1138–1147. https://doi.org/10.1016/j.enpol.2013.07.016.

Public Investment Fund (PIF GIGA PROJECTS, 2018). PIF. Accessed September 25, 2022. https://www.pif.gov.sa/en/Pages/OurInvestments-GigaProjects.aspx .

Sargan, J. Denis. (1964). "Wages and prices in the United Kingdom: a study in econometric modelling." In Hart, P. E., G. Mills, and J.K. Whitaker (eds.), *Econometric Analysis for National Economic Planning*, Butterworths; reprinted in Hendry, D.F. and K.F. Wallis (eds), Econometrics and Quantitative Economics, chapter 10, Basil Blackwell.

Shannak, Sa'd, Jeyhun I. Mikayilov, and Rubal Dua (2024). "Energy price reform to mitigate transportation carbon emissions in oil-rich economies." *Environmental Economics and Policy Studies* 26: 263–283. https://doi.org/10.1007/s10018-024-00400-9.

Saudi Vision 2030. (n.d.). Saudi Diversification Plan. Accessed September 27, 2022. https://www.vision2030.gov.sa/media/rc0b5oy1/saudi_vision203.pdf .

UNFCCC (2021). "Nationally determined contributions under the Paris Agreement." Synthesis report by the secretariat, Glasgow, Scotland.

UNFCCC (2022). "Nationally Determined Contributions." Accessed September 27, 2022. Available at: https://unfccc.int/ndc-information/nationally-determined-contributions-ndcs#:~:text=Nationally%20determined%20contributions%20(NDCs)%20are,the%20impacts%20of%20climate%20change .

Vaidyula, Manasvini and Christina Hood (2018). "Accounting for baseline targets in NDCs: Issues and options for guidance." Climate Change Expert Group, Paper No. 2018(2), OECD. Available at: https://www.oecd.org/environment/cc/Accounting_for_baselines_targets_in_NDCS.pdf .

Vision 2030 (2016). Https://Www.vision2030.Gov.sa/. Saudi Arabia Government. 2016. Accessed September 27, 2022. https://www.vision2030.gov.sa/media/rc0b5oy1/saudi_vision203.pdf .

APPENDIX

This appendix details tests to further validate the choice of the SET III STSM specification used for projecting Saudi Arabia's CO_2 dynamic baselines to 2060. It starts with Section A1 further exploring the choice between the SET I Autometrics specification and the SET III STSM specification. This is followed by Sections A2 and A3 that focus on the SET III STSM specification in terms of the issue of super exogeneity and parameter stability, respectively. This is achieved by re-estimating the SET III STSM specification by OLS since the Fixed Level and the Fixed Slope found for the specification can be replaced by a traditional constant and linear trend but maintaining the interventions of the preferred specification.

A.1 Encompassing tests' results

Further to the model selection procedure discussed in the main text, we also undertook an encompassing model comparison analysis to compare the preferred model from the Autometrics procedure with the preferred model from the STSM procedure. We therefore applied the various encompassing tests proposed by Cox (1961), Sargan (1964), Ericsson (1983), and, similar to Hendry and Santos (2010), a conventional F-test for the joint significance of the coefficients[5] within PcGive 15. The results are presented in Table A1 showing the comparison of Model 1 (M1) the SET I Autometrics specification with Model 2 (M2) the SET III STSM specification where the column headed M1 vs. M2 shows results for the tests of the null hypothesis that M1 encompasses M2 whereas the column headed M2 vs M1 shows results for the tests of the null hypothesis that M2 encompasses M1.

Table A1. Encompassing tests' results.

Test	M1 vs. M2	M2 vs. M1
Cox (1961)	N(0,1) = –10.34 [0.000]**	N(0,1) = –1.740 [0.082]
Ericsson (1983)	N(0,1) = 4.429 [0.000]**	N(0,1) = 1.424 [0.155]
Sargan (1964)	Chi^2(3) = 20.289 [0.000]**	Chi^2(5) = 5.9639 [0.310]
Joint Model	F(3,25) = 21.925 [0.000]**	F(5,25) = 1.2406 [0.320]

Notes: p-values are in parentheses; ** stands for the rejection of the null hypothesis at a 5% significance level.

Table A1 shows that there is not enough evidence to reject the null hypothesis that M2 encompasses M1. However, the null hypothesis that M1 encompasses M2 is rejected by all the tests. This suggests that M2 (the SET III STSM specification) has additional information that is not available in M1 (the SET I Autometrics specification). Adding further support to the decision discussed in the main text for using M2, the SET III specification, to underpin the CO_2 baseline projections.

A2. Testing super exogeneity

As discussed in Hendry and Santos (2010), the reliability of forecasts, and scenario projections of the conditional models require super exogeneity. We, therefore, further test the SET III STSM specification using the Hendry and Santos (2010) approach that uses the impulse saturation idea. Namely, the selected impulses for the marginal models should not be statistically significant

5. Hendry and Santos (2010), suggested this additional alternative Joint Model test. Where the independent variables (excluding the constant and dummy variables) are included in a competing model to the main model and the joint significance of all their coefficients tested.

in the conditional (main) model. We, therefore, refer to our selected SET III STSM specification as the conditional model. The marginal models are models for the independent variables and we select marginal models for each variable using the same structure. In other words, we add all the variables with their first lagged values as right-hand side variables. Following Hendry and Santos (2010), the selection is made at the 1% significance level, and the selected marginal models for GDP, Price, and SRV_SH are as follows:[6]

$$\begin{aligned} gdp_t = {} & 0.4826^{***} gdp_{t-1} + 5.3254^{***} + 0.3654^{***} CO_{2_{t-1}} - 0.1457^{***} Irr_{1985} \\ & -0.1300^{***} Irr_{1987} + 0.0874^{**} Irr_{1991} - 0.0890^{**} Irr_{2002} \end{aligned} \qquad \text{(A1)}$$

$$\begin{aligned} p_t = {} & 0.9983^{***} p_{t-1} + 0.3824^{**} CO_{2_{t-1}} - 0.5798^{**} gdp_t + 6.1278^{**} + 0.6230^{***} Irr_{1995} \\ & -0.2400^{***} Irr_{2007} + 0.3449^{***} Irr_{2016} + 0.3879^{***} Irr_{2018} \end{aligned} \qquad \text{(A2)}$$

$$\begin{aligned} SRV\_SH_t = {} & 0.4854^{***} SRV\_SH_{t-1} + 1.0380^{***} - 0.0259 CO_{2_t} + 0.0710^{***} CO_{2_{t-t}} \\ & -0.0612^{***} gdp_t - 0.0121^{***} p_t + 0.0139^{***} Irr_{1991} + 0.0134^{***} Irr_{1992} \\ & -0.0060 Irr_{1995} - 0.0109^{**} Irr_{1996} + 0.0172^{***} Irr_{2018} + 0.0226^{***} Irr_{2019} \end{aligned} \qquad \text{(A3)}$$

Eleven different impulse indicators are selected for equations (A1), (A2), and (A3) and their impulses from equations in the conditional model tests, excluding the intervention dummy variables.

$$\begin{aligned} CO_{2_t} = {} & -0.1365^{***} p_t + 0.3200^{***} gdp_t - 0.0627 gdp_{t-1} + 0.1439 SRV_{SH_t} \\ & +0.9868^{***} \hat{\gamma}_t - 0.0321 Irr_{1985} + 0.0216 Irr_{1987} + 0.0074 Irr_{1991} + 0.0210 Irr_{1992} \\ & -0.0114 Irr_{1995} + 0.0020 Irr_{1996} - 0.0260 Irr_{2007} + 0.0045 Irr_{2016} \\ & -0.0954^{**} Irr_{2018} - 0.1158^{**} Irr_{2019} + F(11,16) = 1.7856 (p = 0.1416) \end{aligned} \qquad \text{(A4)}$$

The F-test shows that the null hypothesis of super exogeneity (that all the coefficients of the impulse dummies from the marginal models are jointly insignificant in the conditional model) is not rejected, suggesting that GDP, P, and SH_SRV are super exogeneous for the parameters of the main model. Although there are two impulses common in our conditional model and for the marginal models the test does not show any evidence against the super exogeneity of the variables (the two common impulses are I2002 in the GDP equation, and I2007 in the price equation). [7] In summary, these additional tests illustrate that super exogeneity is upheld for the SET III STSM specification, which is used to underpin the CO_2 baseline projections.

A3. Stability tests for the model parameters

The reliability of forecasts, and scenario projections is also dependent upon the stability of the estimated parameters of the specification used to generate the CO_2 projections. We, therefore, further test the stability of the SET III STSM estimated parameters using the CUSUM and CUSUM of squares tests, as well as the recursive estimation procedure of the coefficients (Brown et al., 1975)

6. Note, although the estimation was undertaken using Autometrics the terminology for the interventions from the STSM approach is retained for consistency given it is the STEP III STSM specification being considered.

7. Hendry and Santos (2010) also found one impulse entering the conditional and marginal models.

with the results reported in Figures A1-A2. That does not provide any evidence to suggest that the estimated parameters are unstable. Thus, again, these additional tests illustrate that the SET III STSM would be suitable to underpin the CO_2 baseline projections in the main text.

Figure A1. CUSUM (a) and CUSUM of squares (b) tests for the parameter stability.

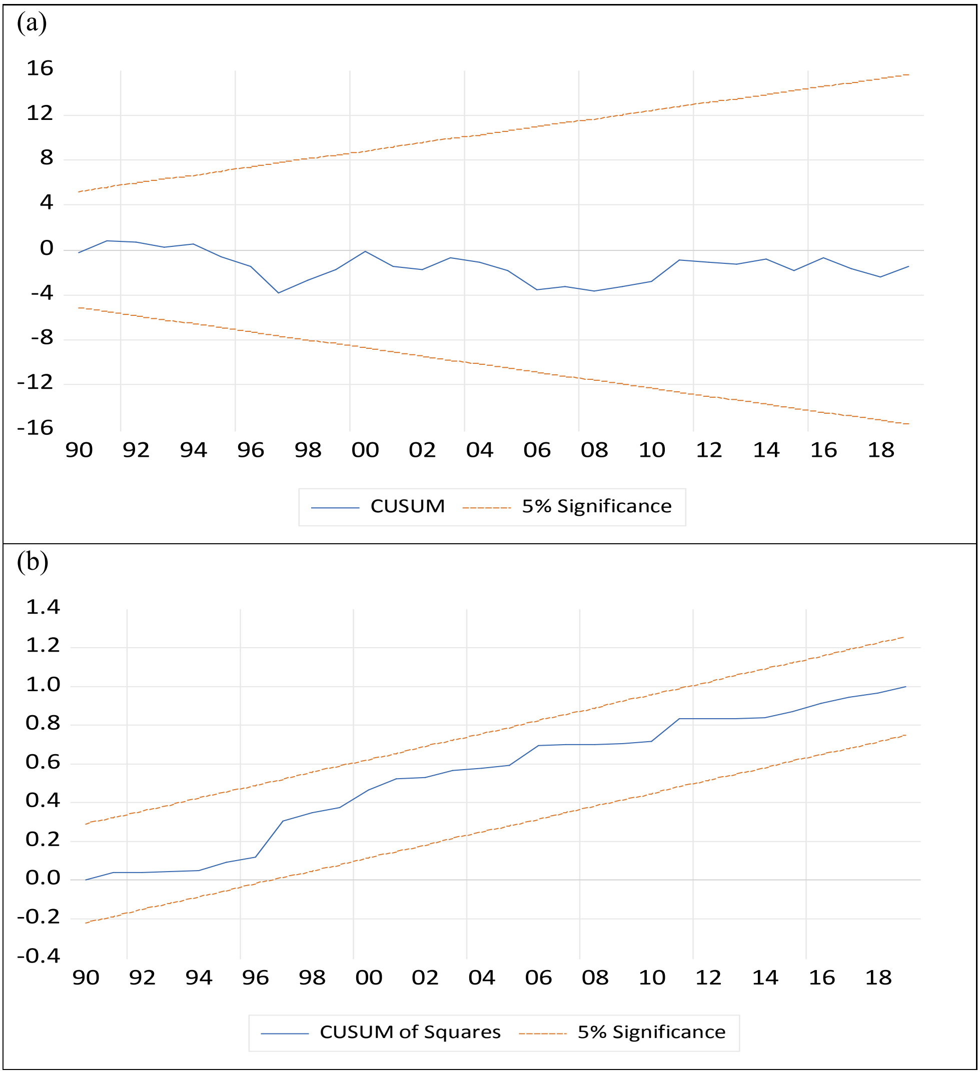
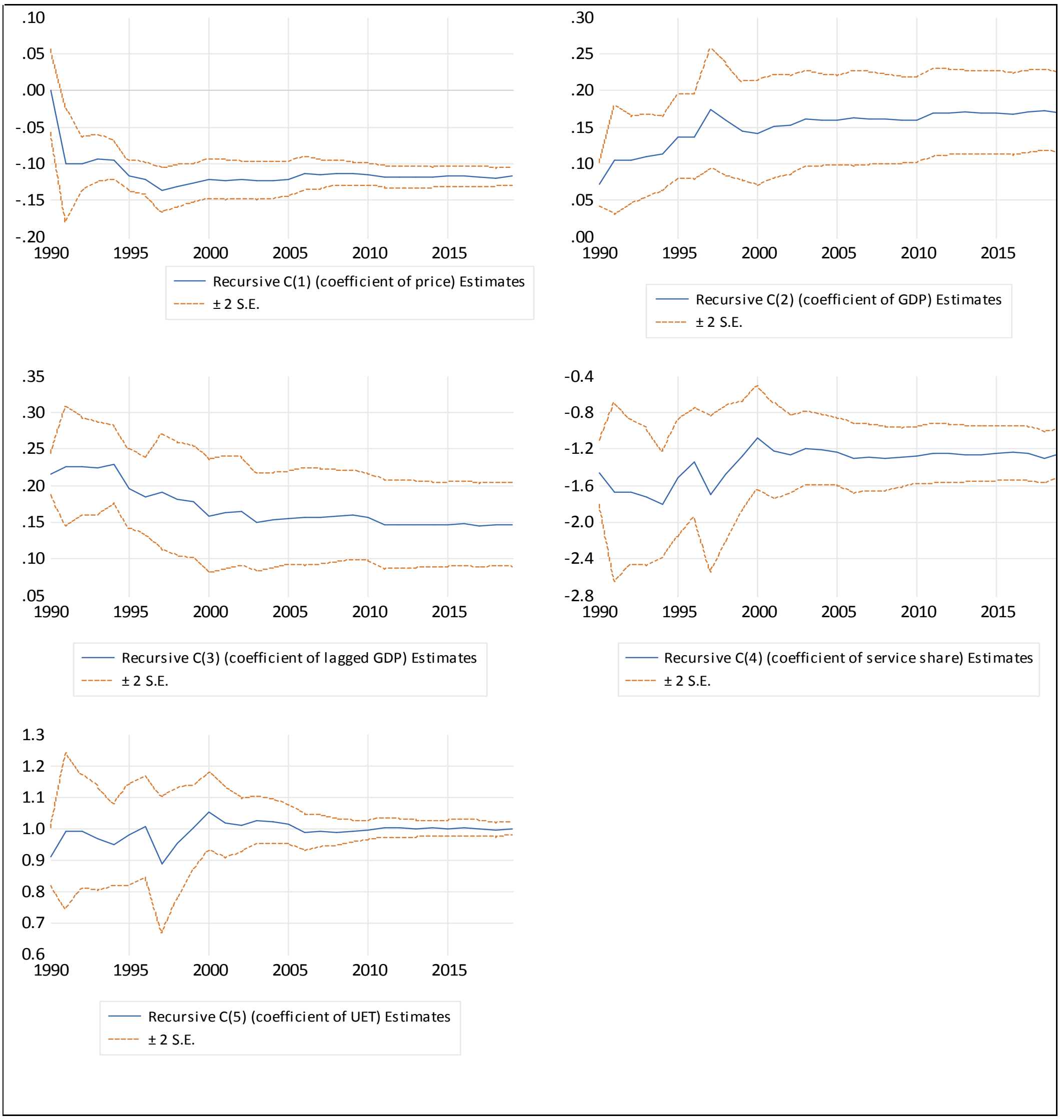


Figure A2. Recursive estimation tests for the stability of coefficients.



IAEE

International Association for
ENERGY ECONOMICS

Membership in the International Association for Energy Economics is open to anyone worldwide who has an interest in the fields of energy or energy economics. Our membership consists of those working in both the public and private sectors including government, academic and commercial. Our current member base consists of 3900+ members in over 110 nations, with 28 nations having local affiliate organization.

We are an independent, non-profit, global membership organization for business, government, academic and other professionals concerned with energy and related issues in the international community. We advance the knowledge, understanding and application of economics across all aspects of energy and foster communication amongst energy concerned professionals.

We are proud of our membership benefit offerings, which include access to a rich library of energy economics related publications and proceedings as well as a robust line-up of webinars, podcasts and conferences. Learn more about the benefits of membership at: https://www.iaee.org/en/membership/benefits.aspx

In addition to traditional membership, we offer student and institutional memberships.