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

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Key Points

We use an econometric model to generate scenario projections of CO_2 emissions under different sets of assumptions on the underlying drivers. These drivers include GDP, energy prices, economic structure, and the underlying emissions trend (UET), which captures the combined effect of exogenous factors such as consumer behavior and energy efficiency.

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 addition to our baseline scenario, we generate CO_2 emissions projections across 10 different scenarios, illustrating how each underlying driver, such as GDP, separately influences future CO_2 emissions in Saudi Arabia.

Given the emphasis that the Saudi nationally determined contribution (NDC) places on economic growth and development, we show that in a high-GDP-growth scenario, CO_2 emissions would grow to 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.

Given the emphasis that the Saudi NDC also places on the economic structure, we show that in an economic diversification scenario, CO_2 emissions would grow to 602 Mt in 2030 and 769 Mt in 2060. In contrast, in a heavy-industrialization scenario, CO_2 emissions would grow to 646 Mt in 2030 and 1096 Mt in 2060. The two scenarios differ by 46 Mt for 2030 and 327 Mt for 2060, underscoring the important impact of economic structure.

In our highest-emissions scenario, in which GDP grows fastest, the economy becomes more heavily industrialized, and energy prices decline in real terms, CO_2 emissions grow to 666 Mt in 2030 and 1,391 Mt by 2060. On the other hand, in our lowest-emissions scenario, in which GDP grows slowest, energy prices are reformed, and the economy diversifies, CO_2 emissions decline to 516 Mt in 2030 and 465 Mt by 2060. Even in the latter scenario, further efforts would be needed to meet the net-zero objective.

Summary

As a party to the Paris Agreement, which aims to limit the global average temperature rise to below 2 degrees and keep it as close as possible to 1.5 degrees Celsius, Saudi Arabia has submitted its nationally determined contribution (NDC). NDCs are essentially climate action plans that encompass a party's climate target and the initiatives or policies that it plans to implement to achieve that target. NDCs lie "at the heart of the Paris Agreement" and are submitted at 5-year intervals, with each successive NDC (referred to as either a new or an updated NDC) reflecting higher ambition. Saudi Arabia has thus far participated in two successive rounds of NDC submissions. In its most recent updated NDC, submitted in 2021, Saudi Arabia announced its new pledge to reduce greenhouse gas (GHG) emissions by 278 million tons (Mt) of carbon dioxide (CO_2) equivalent (eq) annually by 2030.

Saudi Arabia's NDC emission target is expressed as a reduction below a baseline or business-as-usual emissions growth scenario. A country's baseline is a counterfactual scenario that shows how emissions would evolve under the assumption that "no mitigation policies or measures will be implemented beyond those that are already in force and/or are legislated or planned to be adopted". Although Saudi Arabia has not yet publicly disclosed a quantitative baseline in its NDC, it has provided qualitative details on its baseline, which it refers to as "dynamic baselines". 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, driven by its oil exports, with oil export revenues "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."

This paper contributes to the understanding of how emissions may evolve in Saudi Arabia through 2030 and up to 2060 by producing various dynamic emissions scenarios. These include a baseline emissions scenario, demonstrating how different variables, such as gross domestic product (GDP), energy prices, and economic structure, influence the evolution of CO_2 emissions in Saudi Arabia. We focus on CO_2 emissions only, which account for approximately 80%–90% of total GHG emissions in Saudi Arabia. We generate our CO_2 emissions projections using econometric methods. Specifically, we estimate equations using Autometrics and the structural time series model (STSM), two methods that can explain emissions data through a combination of trends, interventions[1], and right-hand-side variables such as GDP and energy prices.

Using both methods, we estimate multiple equations that include different right-hand-side variables. Our econometric results reveal that the coefficients on variables such as GDP and energy prices are consistent across the estimated equations, which indicates the robustness of the estimates. 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 that 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, economic structure, and the underlying emissions trend (UET), which captures the combined effect of exogenous factors such as consumer behavior and energy efficiency. We build 11 scenarios, including the baseline scenario that acts as a reference, showing how CO_2 emissions might evolve in Saudi Arabia without any additional policy efforts under the assumption that the underlying drivers continue to evolve in the future as they did in the past. We generate our baseline CO_2 emissions projection by plugging the baseline assumptions on the evolution of drivers such as GDP into our preferred econometric model. In our baseline, Saudi CO_2 emissions would rise from 540 Mt in 2019 to 621 Mt in 2030 and 878 Mt in 2060.

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

In addition to the highest- and lowest-emissions scenarios, we highlight how the underlying drivers can separately influence CO_2 emissions. Given the emphasis that the Saudi NDC placed on economic structure and development, we highlight how these two variables separately influence 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 grow 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. The two scenarios differ by 46 Mt for 2030 and 327 Mt for 2060, underscoring the impact of GDP composition 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 economic structure and development in its updated NDC.

In short, our paper generates several key insights for policymakers. First, it highlights how different variables, such as GDP and energy prices, influence CO_2 emissions projections. Second, it reveals the critical role that the economic structure can play, especially in a country undergoing rapid economic transformations such as Saudi Arabia. Third, it 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 such as direct air capture. These additional efforts will be necessary for the Kingdom of Saudi Arabia to achieve its goals of reaching net zero and securing a sustainable future.

Introduction

As a party to the Paris Agreement, which aims to limit the global average temperature rise to below 2 degrees and keep it 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 that encompass a party's climate target and the initiatives or policies that it plans to implement to achieve that target. NDCs lie "at the heart of the Paris Agreement" and are submitted at 5-year intervals, with each successive NDC (referred to as either a new or an updated NDC) reflecting higher ambition (UNFCCC, 2022).

Saudi Arabia has thus 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 reduce GHG emissions by 278 Mt CO_2eq annually by 2030 (Kingdom of Saudi Arabia, 2021, p. 2). Saudi Arabia has 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 scenarios as baseline projections, which many developing countries appear to prefer. In contrast, other countries, especially developed countries, appear to prefer what are commonly known as absolute targets, which are expressed as a reduction below the emissions level in a specified historical base year. According to the United Nations Framework Convention on Climate Change's (UNFCCC's) (2021) NDC Synthesis Report, in 2021, 53% of updated NDCs contained absolute emission reduction targets, 38% contained baseline targets, and 9% contained a different type of target.

A country's baseline or business-as-usual scenario is a counterfactual scenario showing how emissions would evolve under the assumption that "no mitigation policies or measures will be implemented beyond those already in force and/or are legislated or planned to be adopted" (IPCC, 2022). In its definition of baseline scenarios, the IPCC (2022) adds 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."

Some parties 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. For example, gross domestic product (GDP) appears to be a common key variable in most parties' baseline scenarios, as different economic growth rates will lead to different emissions growth scenarios.

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 scenario for CO_2 emissions, such as GDP, economic structure, energy consumption patterns, the energy mix, and the energy price. Furthermore, the choice of method used to project baseline emissions can significantly influence their trajectory. Given these uncertainties, some parties to the Paris Agreement have released the specific modeling tools that they used to estimate their baseline or business-as-usual emissions scenarios (UNFCCC, 2021).

Although Saudi Arabia is one of the countries that has not yet publicly disclosed a quantitative baseline in its NDC, it has provided qualitative details on its baseline, which it refers to as “dynamic baselines” (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 occurring in the country over the coming years. Specifically, Saudi Arabia has envisioned two distinct but plausible baseline scenarios. In the first, which is taken as the default scenario, Saudi Arabia achieves economic diversification, driven by its oil exports, with oil export revenues “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.” These two different scenarios appear to influence future emissions by influencing the future economic structure.

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 in the future, 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, which will reduce demand for energy and emissions and encourage 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 as tourism and nonoil 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 the understanding of how emissions may evolve in Saudi Arabia through 2030 and up to 2060 by producing various dynamic emissions scenarios, including a baseline emissions scenario, demonstrating how different variables, such as GDP, energy prices, and economic structure, influence the evolution of CO_2 emissions in Saudi Arabia. We focus on CO_2 emissions only, which account for approximately 80%–90% of total GHG emissions in Saudi Arabia. We construct our CO_2 emissions scenarios using econometric methods. Specifically, we estimate equations using both Autometrics and the structural time series model (STSM), two methods that can explain emissions data through a combination of trends, interventions, and right-hand-side variables such as GDP and energy prices.

Our preferred econometric equation shows 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. In line with Saudi Arabia’s NDC, we illustrate the impact of economic structure on Saudi Arabia’s baseline emissions. Our increasing-economic-diversification and increasing-heavy-industrialization scenarios differ by 43 $MtCO_2eq$ in 2030 and 328 $MtCO_2eq$ in 2060, highlighting the potentially critical role of economic diversification paths, especially in the long term. Furthermore, we construct upper- and lower-bound scenarios in which emissions rise to 1,391 $MtCO_2eq$ versus 465 $MtCO_2eq$ in 2060, respectively, underscoring the large, combined impact that variables such as GDP, energy prices, economic structure, and energy efficiency and behavioral change can have on CO_2 emissions in Saudi Arabia.

Methodologies and Data

To reveal the relationships between CO_2 emissions and their potential drivers, we use the STSM approach (Harvey, 1989) and the general-to-specific modeling (Gets) approach (see Hendry and Doornik, 2014, inter alia). The details of the methods and techniques used are provided in Appendix A2.

Table 1 below reports summary statistics of the data used in estimations. Co2 is total CO_2 emissions, gdp stands for gross domestic product, p is the average energy price, and srv_sh represents the share of services in GDP. Details and sources on the mentioned variables can be found in Appendix A2.2.

Table 1. Summary statistics.

	(1)	(2)	(3)	(4)	(5)
Variables	N	Mean	SD	Min	Max
CO_2	36	5.671	0.468	4.897	6.357
GDP	36	14.25	0.358	13.56	14.79
p	36	6.509	0.339	5.802	7.117
srv_sh	36	0.666	0.0143	0.643	0.706

Source: GaStat, Enerdata, and Authors' Calculation.

Results and Scenarios

Estimated Econometric Model for Projections

Full details of the estimation and choice of equation used to underpin the scenarios are given in the appendix. In brief, the preferred equation relates the natural logarithm of CO_2 emissions (denoted by co_{2_t}) in year t to the natural logarithm of GDP (gdp_t), the lag of the natural logarithm of GDP (gdp_{t-1}), the natural logarithm of the real energy price (p_t), and the share of services in nonoil GDP (SRV_SH_t). This is estimated by STSM and is given by:

$$\widehat{co_{2_t}} = \hat{\gamma}_t + 0.1694^{***} gdp_t + 0.1461^{***} gdp_{t-1} - 0.1174^{***} p_t - 1.2455^{***} SRV\_SH_t \quad (1a)$$

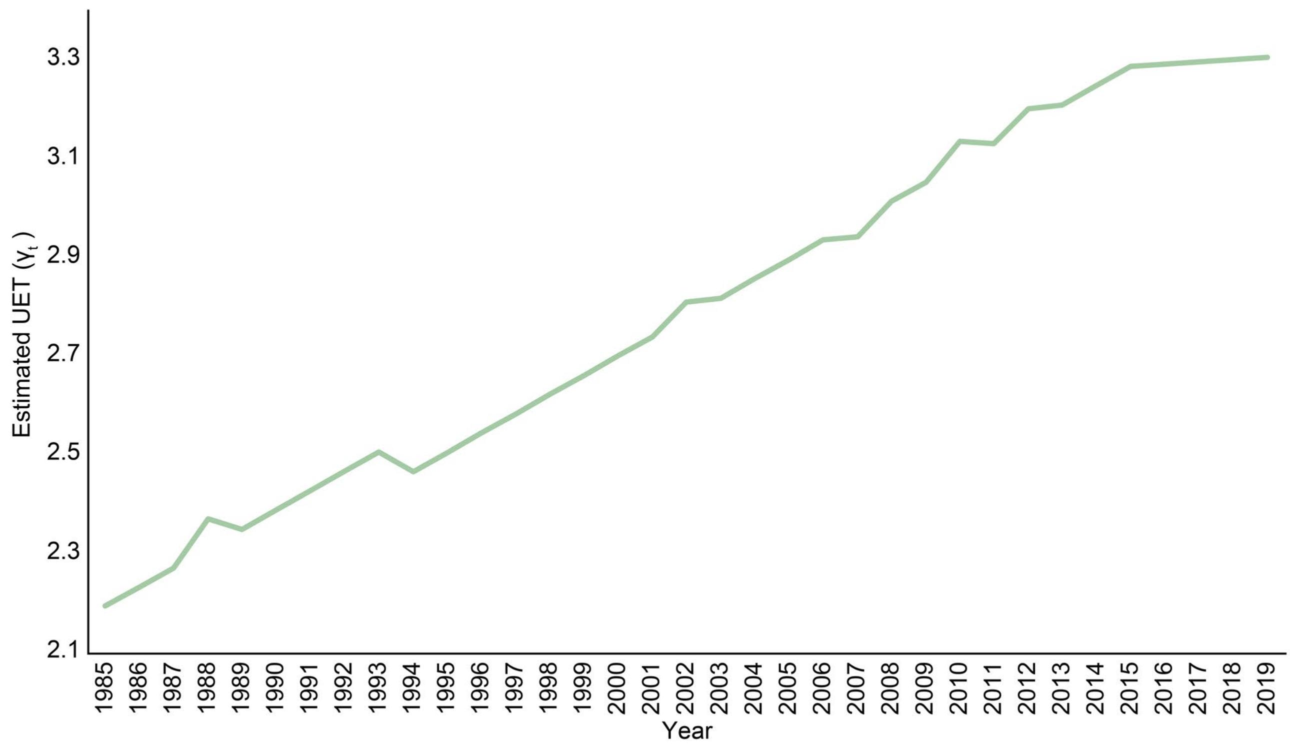
with the estimated UET ($\hat{\gamma}_t$, shown in Fig. 1) given by:

$$\hat{\gamma}_t = \hat{\mu}_t - 0.0594^{***} Irr_{1988} - 0.0798^{***} Lvl_{1994} + 0.0307^{**} Irr_{2002} - 0.0327^{***} Irr_{2007} + 0.0435^{***} Irr_{2010} + 0.0309^{**} Irr_{2012} - 0.0346^{***} Slp_{2016} \quad (1b)$$

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 $\hat{m}_t$ represents the estimated level component of the trend.

The estimated equation suggests that in the long run, a one percent increase in GDP would increase CO_2 emissions by 0.32%. A 1% increase in the real

Figure 1. Estimated UET ($\hat{\gamma}_t$) for the preferred model.



Source: Estimation results.

energy price would reduce CO_2 emissions by 0.12%, and a one-percentage-point increase in the share of services value added in nonoil GDP would reduce CO_2 emissions by 1.25%. Furthermore, the estimated UET at the end of the estimation period (and therefore within the baseline projection) suggests that with GDP, the real energy price, and the share of services value added in nonoil GDP held constant, there would be an autonomous increase in CO_2 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. 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 the bulk of these countries' energy-saving behavior (80%–90%) has not been accounted for. The underlying energy demand trend is also historically upward sloping for Saudi Arabia; see Aldubayan and Gassim (2020) for further details.

Scenario Construction

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

Initial Saudi GDP projections are 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 implies that the Saudi economy will 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, under which the Saudi economy would triple in 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 picks up a recent announcement of price changes in Saudi Arabia (Arab News, 2022). This announcement stated that by the fourth quarter of 2023, the government will implement price adjustments for natural gas, Arab heavy crude oil, ethane, heavy fuel oil, and Arab light crude oil. In addition, the government will review these prices annually up to 2030. From 2030 onward, 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 toward services. We design our low, central, and high scenarios from the perspective of the share of services. Our central-services-share 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 the baseline scenario, as it extends the observed historical trends in the composition of the Saudi economy (GaSTAT, 2020). Our low-services-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-services-share scenario, the services share grows to 75% of the Saudi economy by 2060, in line with the trend in several developed economies, while the manufacturing share declines to 14% by 2060 (Herrendorf, Rogerson, and Valentinyi 2013).

Last, 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. 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. Our high-UET scenario, an unlikely scenario, assumes a change in these exogenous factors that makes the UET more steeply 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 steeply 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 impact of the UET 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.

Baseline Projection

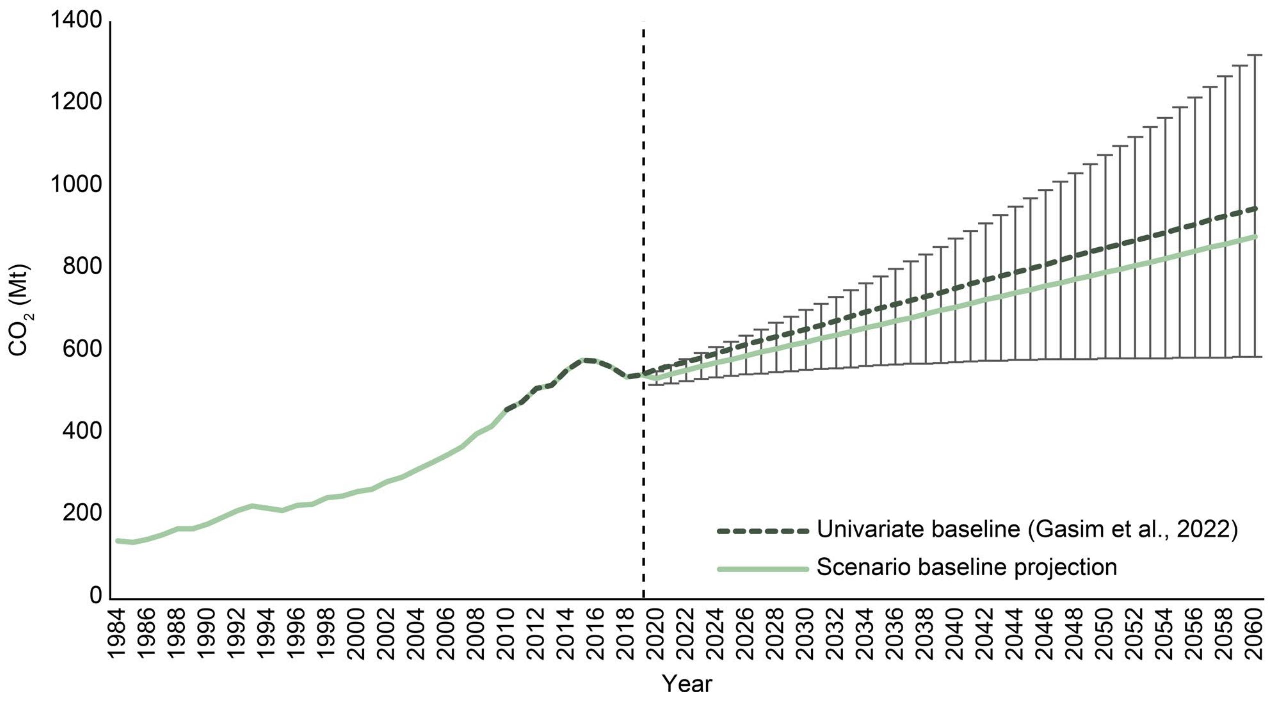
Before considering the other scenarios, we present our baseline scenario projection, which acts as a reference, showing how CO_2 emissions might evolve without any additional policy efforts should the underlying drivers continue to evolve in the future as they did in the past. Our baseline scenario rests on assumptions about how GDP, energy prices, the services share, and other exogenous factors captured by the UET evolve until 2060. Our baseline scenario assumptions, described previously, essentially extend past historical trends into the future. By plugging these assumptions into our preferred econometric model, we generate our baseline scenario, which is presented in Fig. 2. 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 Fig. 2 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 Gasim et al.'s (2022) projection and is within the statistical confidence interval of their baseline projection shown in Fig. 2.

Scenario Projections

In addition to the baseline, it is important to showcase how different pathways of economic growth, economic diversification, and energy price and energy efficiency changes, among other factors, influence future CO_2 emissions in Saudi Arabia. Table 2 lists the different assumptions on the underlying drivers and highlights the CO_2 emissions projections generated under each scenario by plugging those assumptions into the preferred econometric model. As presented previously, our baseline scenario yields a CO_2 emissions projection of 621 Mt in 2030 and 878 Mt in 2060.

Increasing the GDP growth rates while keeping all other underlying drivers fixed at their baseline values leads to a CO_2 emissions projection that rises to 635 Mt in the high-GDP scenario. In contrast, decreasing the GDP growth rates yields a projection that rises to only 607 Mt by 2030. Although the gap between the low- and high-GDP scenarios is fairly small in

Figure 2. CO_2 baseline projection.



Source: Gasim et al. (2022).

2030 (28 Mt), the gap grows to 204 Mt by 2060, the year in which the net-zero objective is targeted to be achieved.

Increasing energy prices above their level in the low-energy-price scenario, which is designated as the baseline, leads to scenarios with lower CO_2 emissions. If we assume flat energy prices in real terms (the central-energy-prices scenario), CO_2 emissions will grow to 611 Mt by 2030, approximately 10 Mt below the baseline scenario value in 2030. With the implementation of energy price reforms under the high-energy-prices scenario, CO_2 emissions in 2030 will grow to only 564 Mt, which is almost 60 Mt lower than the baseline, highlighting the large potential impact of energy price reform, even in the near term. In the long term, the gap between the high-energy-prices scenario and the low-energy-prices scenario (i.e., the baseline) becomes 134 Mt.

The composition of GDP, as captured by the services share, has a significant impact on CO_2 emissions. Under the low-services-share scenario, manufacturing grows rapidly to 40% by 2060, while the services sector grows slowly to 49% only, yielding CO_2 emissions of 646 Mt in 2030 and 1,096 Mt in 2060. The low-services-share scenario presented here is aligned with the heavy-industrialization scenario presented in Saudi Arabia's NDC as one of its dynamic baselines. In contrast, if the services sector were to grow to 75% of GDP by 2060, emissions would be 602 Mt (46 Mt less than in the heavy-industrialization scenario) in 2030 and 769 Mt in 2060 (327 Mt less than in the heavy-industrialization scenario). The high-services-share scenario presented here is aligned with the economic diversification scenario presented in Saudi Arabia's NDC as one of its dynamic baselines. In summary, our findings underscore the impact of GDP composition on CO_2 emission projections, revealing why the Saudi government emphasized this factor in its updated NDC.

The UET, which captures the combined impact of multiple exogenous factors, is varied to reveal how these exogenous factors could influence CO_2 emission projections. In the low-UET scenario (a steeper downward-sloping UET), which may capture accelerated improvements in energy efficiency and changes in behavior that reduce emissions, CO_2 emissions grow to 616 Mt in 2030 and 776 Mt in 2060. In the high-UET scenario (a steeper upward-sloping UET), CO_2 emissions grow to 626 Mt in 2030 and 992 Mt in 2060. Our findings reveal that beyond the economic factors considered previously, other factors could play a large role in influencing the evolution of CO_2 emissions in Saudi Arabia.

Finally, we introduce our highest-emission and lowest-emission scenarios, which reflect the combination of assumptions on each underlying driver that yields the highest and lowest CO_2 emissions projections, respectively. Under the highest-emission scenario, GDP grows fastest, the economy becomes more heavily industrialized, energy prices decline in real terms, and the UET grows more upward sloping. With this combination of assumptions, CO_2 emissions would grow to 666 Mt in 2030 and 1,391 Mt by 2060. On the other hand, under our lowest-emission scenario, GDP grows slowest, energy prices are reformed, the economy diversifies toward 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.

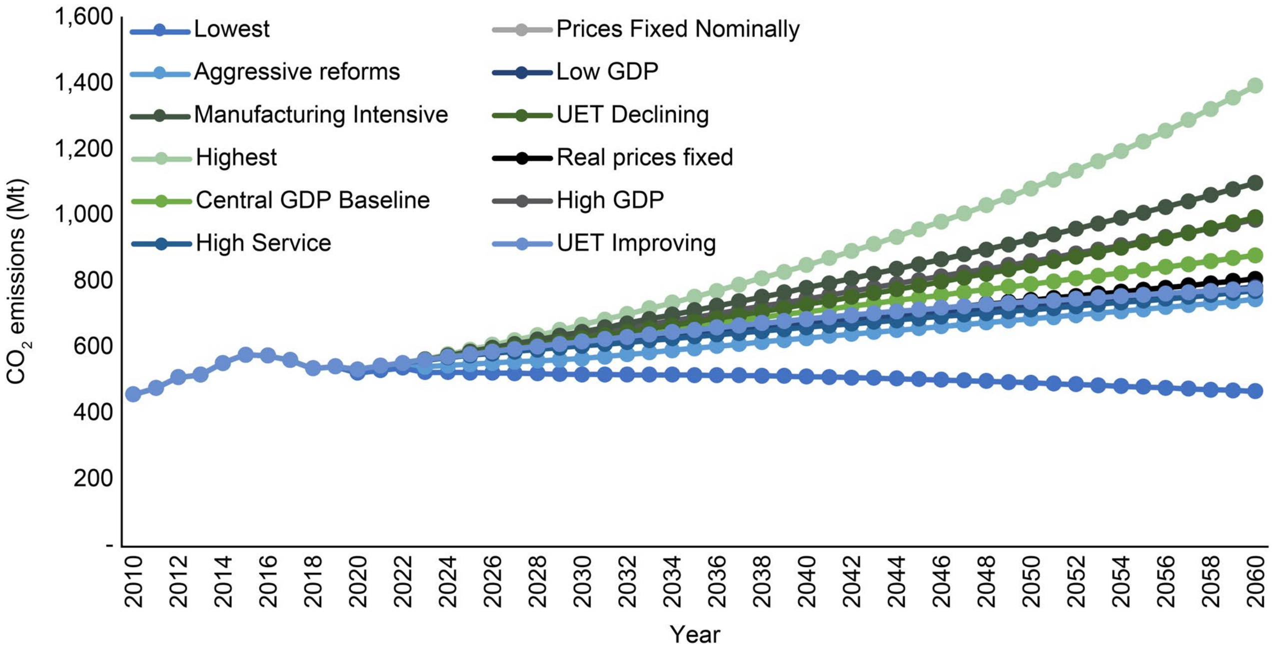
Table 2. Scenario assumptions for CO_2 projections.

Scenario	GDP real average growth 2020–2060:	Energy prices:	Services share by 2060:	Underlying emission trend:	CO_2 emission 2030	CO_2 emission 2060
Baseline	2.2% (central)	Fixed in nominal terms (low)	62% (central)	Last observed slope (central)	621 Mt	878 Mt
High GDP	3.1% (high)	Fixed in nominal terms (low)	62% (central)	Last observed slope (central)	635 Mt	985 Mt
Low GDP	1.2% (low)	Fixed in nominal terms (low)	62% (central)	Last observed slope (central)	607 Mt	781 Mt
High energy prices	2.2% (central)	Increasing up to 2030 then fixed in real terms (high)	62% (central)	Last observed slope (central)	564 Mt	744 Mt
Central energy prices	2.2% (central)	Fixed in real terms (low)	62% (central)	Last observed slope (central)	611 Mt	805 Mt
Low Service	2.2% (central)	Fixed nominally (low)	49% (low)	Last observed slope (central)	646 Mt	1,096 Mt
High Service	2.2% (central)	Fixed nominally (low)	75% (high)	Last observed slope (central)	602 Mt	769 Mt
Low UET	2.2% (central)	Fixed nominally (low)	62% (central)	Slope declining annually below last observed value (low)	616 Mt	776 Mt
High UET	2.2% (central)	Fixed nominally (low)	62% (central)	Slope increasing annually above last observed value (high)	626 Mt	992 Mt
Lowest emissions	1.2% (low)	Increasing up to 2030 then fixed in real terms (high)	75% (high)	Slope declining annually below last observed value (low)	516 Mt	465 Mt
Highest emissions	3.1% (high)	Fixed in nominal terms (low)	49% (low)	Slope increasing annually above last observed value (high)	666 Mt	1,391 Mt

Source: Authors' analyses.

Fig. 3 below 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 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 will need to improve, for Saudi Arabia to achieve its net-zero ambition.

Figure 3. Fan chart of CO_2 emission projections for Saudi Arabia (all scenarios).



Source: Authors' analyses.

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. Therefore, it requires a quantitative baseline scenario showing how emissions would evolve if no further policies or actions were implemented. Although Saudi Arabia is one of the countries that has not yet publicly announced a quantitative baseline in its NDC, it has provided qualitative details on its baseline, which it refers to as "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 occurring in the country over the coming years.

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

We model CO_2 emissions by utilizing the general-to-specific approach via STSM and Autometrics, two econometric methods that allow 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 robustness of the estimates. 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 that 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 under the assumption that the underlying drivers continue to evolve in the future as they did in the past. We generate our baseline CO_2 emissions projection by plugging the baseline assumptions on the evolution of drivers such as GDP 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 CO_2 emissions scenarios highlight how different factors could affect CO_2 emissions in Saudi Arabia up to 2060. The gap between the highest-emissions and lowest-emissions projections underscores how much emissions could evolve differently depending on the underlying drivers. In the highest-emissions scenario, in which GDP grows fastest, the economy becomes more heavily industrialized, energy prices decline in real terms, and the UET grows more steeply upward sloping, CO_2 emissions grow to 666 Mt in 2030 and 1,391 Mt by 2060. On the other hand, in the lowest-emissions scenario, in which GDP grows slowest, energy prices are reformed, the economy diversifies, and the UET becomes more steeply downward-sloping, CO_2 emissions decline to 516 Mt in 2030 and 465 Mt by 2060.

In addition to the highest- and lowest-emissions scenarios, we highlight how the underlying drivers can separately influence CO_2 emissions. Given the emphasis that the Saudi NDC places on the economic structure and economic development, we highlight how these two variables separately influence 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 grow 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 grow to 602 Mt in 2030 and 769 Mt in 2060. This high-services-share scenario is aligned with the economic diversification scenario presented in Saudi Arabia's NDC. The two scenarios differ by 46 Mt for 2030 and 327 Mt for 2060, underscoring the impact of GDP composition on CO_2 emission projections. Similarly, we show that in the high-GDP-growth scenario, CO_2 emissions would grow to 635 Mt in 2030 and 985 Mt in 2060, while in the 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.

To conclude, our paper generates several key insights for policymakers. First, it highlights how different variables, such as GDP and energy prices, influence CO_2 emissions projections. Second, it reveals the critical role that economic structure can play, especially in a country undergoing rapid economic transformations such as Saudi Arabia. Third, it 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 such as direct air capture. These additional efforts will be necessary for the Kingdom of Saudi Arabia to achieve its goals of reaching net zero and securing a sustainable future.

Endnote

[1] Interventions here refer to dummy variables that are included in a model to account for outliers.

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Appendix

A.1. Literature Review

At the heart of this research are the climate change problems caused by greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2) emissions, given that they represent a substantial share of total GHG emissions. Not surprisingly, therefore, the study of CO_2 emissions is a significant part of research devoted to environmental issues. As countries look 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 overall CO_2 emissions–related studies. To the best of our knowledge, no previous journal papers have focused on multivariate modeling of total CO_2 emissions for Saudi Arabia using time series data. There are, however, several papers that use panel data that cover Saudi Arabia. Considering the vast number of papers modeling CO_2 emissions, in this study, we review only a sample of the papers that include Saudi Arabia. In addition, since the main target of this study is to construct scenario simulations/forecasts, we focus on papers dealing with forecasting. For 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, as well as petroleum consumption, natural gas consumption, and electricity consumption, using data ranging 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 forecasts, and their data are outdated and do not capture the behavior of CO_2 emissions in recent years. In addition, these authors modeled only fuel-based CO_2 emissions, not total CO_2 emissions. Usama Al-Mulali and Tang (2013) modeled CO_2 emissions for GCC countries, including Saudi Arabia, using data from 1980 to 2009 and found a Saudi-specific income elasticity of 0.07. Arouri et al. (2012) studied the relationship for a panel of Middle East and North Africa (MENA) countries and concluded that there is an inverted U-shaped relationship for Saudi Arabia (their data span was 1981–2005), which is arguably surprising given Saudi Arabia's stage of development. Mahmood et al. (2022), using data from 1980 to 2019, modeled the CO_2 emissions for Gulf Cooperation Council (GCC) countries, considering the asymmetric impacts. For the Saudi Arabian case, they did not find an asymmetric impact, the coefficient being insignificant for negative income growth. Mahmood et al. (2022) did not perform forecasting exercises. Omri (2013) utilized GCC group data for 1990–2011 and found a monotonically increasing relationship between income and CO_2 emissions, finding 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. Interestingly, unlike Omri (2013), they concluded that there is an inverted U-shaped relationship between income and CO_2 emissions for the Saudi case. Onifade et al. (2020) utilized Organization of Petroleum Exporting Countries (OPEC) members' panel data from between 1990 and 2014 and 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. The common feature of all the papers mentioned above is that they produced projections for the future path of CO_2 emissions. In addition, they used energy consumption as a driver of CO_2 emissions, subject to misleading estimation results, as discussed in Jaforullah and King (2017). Jaforullah and King (2017) showed that using energy consumption to calculate CO_2 emissions and then using the same variable for modeling purposes may yield biased estimation results. Moreover, using some panel data techniques might result in under- or overestimation of the country-specific features of relationships (Kennedy, 2009, p. 285). In addition, based on the reviewed studies, the average income elasticity is approximately 0.40, although the basis for these findings is arguably questionable.

Shannak et al. (2022), using data from 1990 to 2019, modeled transport-specific CO_2 emissions for Saudi Arabia. They also forecasted transport-specific CO_2 emissions until 2030, with their forecast for 2030 being 184 million tons of CO_2 emissions. This paper addresses only transport-related and not total CO_2 emissions.

Since the primary aim of this paper is to construct CO_2 emissions scenario projections for Saudi Arabia, previous papers dealing with this task are considered here. To the best of our knowledge, only three previous studies produced projections for Saudi Arabia's CO_2 emissions: Köne and Büke (2010), Alshammari (2020), and Gasim et al. (2022). Köne and Büke (2010) used simple linear trend analysis to model CO_2 emissions for the top 25 emitters, including Saudi Arabia. They made projections based on low-economic-growth, reference, and high-economic-growth scenarios for CO_2 emissions in 2030, which ranged from 496 to 571 Mt. Through the developed 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 Alshammari's (2020) business-as-usual scenario, Saudi CO_2 emissions would be between 643 Mt and 2156 Mt in 2050. Gasim et al. (2022) produced a baseline scenario for Saudi-specific total CO_2 emissions until 2060, which is the target year for the fulfillment of the country's net-zero emissions objective. Their projections suggest that in 2030 and 2060, Saudi CO_2 emissions could be 678 Mt and 970 Mt, respectively. However, the projections in Gasim et al.'s (2022) work based on a univariate modeling framework were built to provide a baseline projection, not to make simulations for policy scenarios.

Beyond the Saudi-specific studies, Hendry (2020) applied a different strategy and modeling approach to UK CO_2 emissions data from 1860 to 2017. He used a general-to-specific modeling approach and a multipath-search machine-learning technique for modeling purposes and used the capital stock, GDP, oil consumption and coal consumption as potential drivers of CO_2 emissions. Hendry (2020) concluded that the capital stock drives CO_2 emissions in the UK, not GDP. Using the estimated model, Hendry (2020) assessed the achievability of the UK's 2050 target. We apply a strategy similar to Hendry's (2020) in terms of finding the relevant model considering different specifications and using techniques such as the STSM and Autometrics algorithms, enabling broader and more flexible options for parameter estimation.

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

A.2. Methodologies and Data

A.2.1. Overview

We model the natural logarithm of Saudi CO_2 emissions (Mt), denoted by co_{2_t}, as a function of a selection of vectors of drivers, denoted by $\boldsymbol{X}_t$, where t denotes the year. In the general equations, one-year lags of all variables are included to capture autoregressive behavior, and we obtain our "preferred" or "final" equation 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. This model could also be referred to as a "selected" model.

To estimate the various models, we consider two different econometric techniques: Autometrics and the structural time series model (STSM) since these both utilize a combination of trends and interventions but in very different ways. We also consider different sets of explanatory variables for each methodology, all of which are explained below.

A.2.2. Autometrics

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

$$co_{2_t} = \alpha_0 + \alpha_1 co_{2_{t-1}} + \alpha_2 \boldsymbol{X}_t + \alpha_3 \boldsymbol{X}_{t-1} + \sum\nolimits_1^T \vartheta_i IIS_t + \sum\nolimits_1^T \tau_i SIS_t + \sum\nolimits_1^T \varphi_i DIIS_t + \sum\nolimits_1^T \omega_i TIS_t + \varepsilon_t \tag{A1}$$

where co_{2_t} is the natural logarithm of Saudi CO_2 emissions (Mt) in year t, $\boldsymbol{X}_t$ is a vector of drivers in year t, IIS_t is an impulse indicator, SIS_t is a step indicator, $DIIS_t$ is a differenced impulse-indicator saturation dummy, and TIS_t is a trend indicator. a_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 has two parts (see, for example, Castle et al., 2017; Hendry 2020). First, 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 but 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). Second, the chosen dummies from the first stage are fixed with the lagged values of the dependent and independent variables unfixed, and 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%), as suggested by Castle et al. (2021), is utilized for the search. This is all undertaken using the multipath selection procedure embedded in the PcGive-15.10 econometric modeling program (Doornik and Hendry, 2018). This procedure is applied to the four sets of explanatory variables outlined below, and the results are discussed below after we outline the alternative estimation methodology, the STSM.

A.2.3. 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:

$$co_{2_{t_t}} = \gamma_t + \alpha_1 co_{2_{t-1}} + \alpha_2 \boldsymbol{X}_t + \alpha_3 \boldsymbol{X}_{t-1} + \varepsilon_t \tag{A2a}$$

where co_{2_t}, $\boldsymbol{X}_t$, and a_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, σ_ε^2). The stochastic trend consists of a level m_t and a slope b_t, which are defined as follows:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{A2b}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{A2c}$$

where η_t ~ *NID* (0, σ_η^2) and ξ_t ~ *NID* (0, σ_ξ^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. As in Autometrics, different types of dummy interventions can be identified and added to the model (Harvey and Koopman, 1992). These interventions capture important breaks and structural changes during the estimation period at certain dates. These interventions can be incorporated into the stochastic trend, which can be defined as follows:

$$\gamma_t = m_t + \text{irregular interventions } (Irr_t) + \text{level interventions } (Lvl_t) + \text{slope interventions } (Slp_t) \tag{A2d}$$

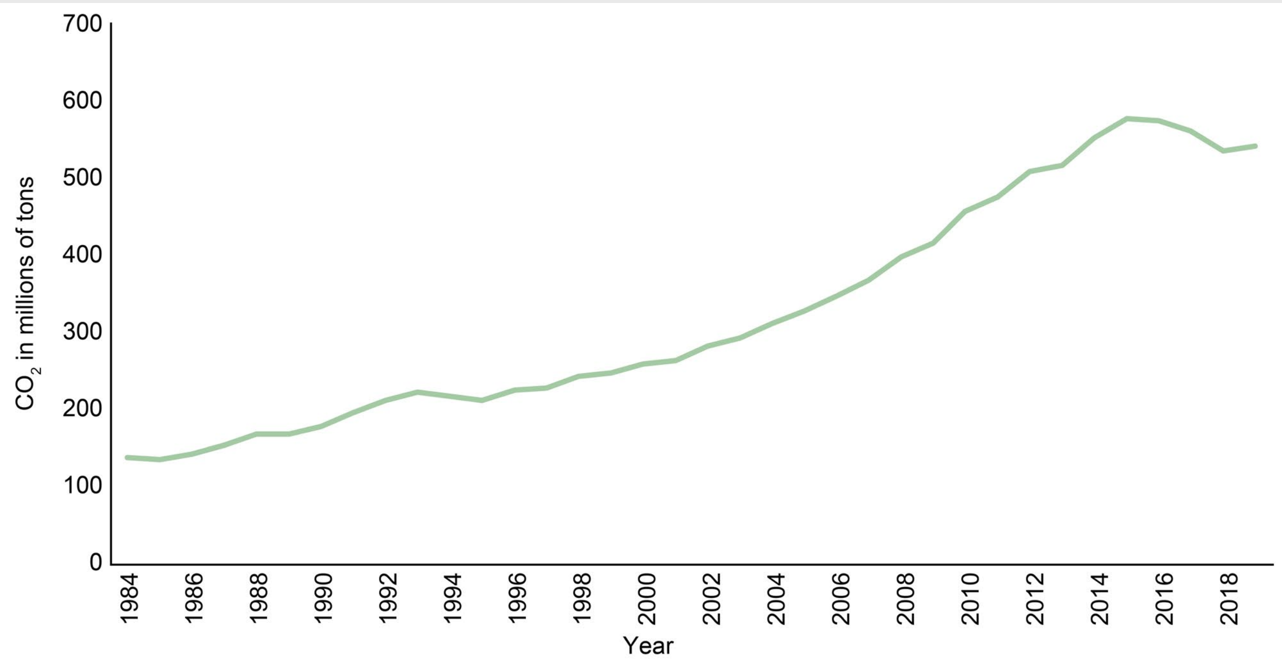
The STSM is also often referred to as the unobserved components model since the trend attempts to capture any systematic influences on the left-hand-side dependent variable not captured by the right-hand-side explanatory variables. Hence, in this case, the trend represents the changes in CO_2 emissions driven by a range of unobserved exogenous or autonomous factors, such as exogenous energy and CO_2 efficiency, changes in environmental command-and-control regulations (i.e., policies that are not market driven), increased environmental education and awareness, cultural changes, and changes in tastes and fashion. The estimated trend was referred to as the underlying energy demand trend when applied to behavioral energy demand functions (Hunt et al., 2003 and Hunt and Ninomiya, 2003), but it 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) the underlying emissions trend (UET), which is the term that we use here.

To estimate the STSM, equations (A2a), (A2b), and (A2c) are initially estimated by maximum likelihood along with the Kalman filter in 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 are excluded while we ensure both that the model passes a range of diagnostic tests (detailed in the results below) and that the auxiliary residuals associated with the irregular, level, and slope components do not suffer from nonnormality. Consistent with the Autometrics estimation, this approach is applied to four sets of explanatory variables, and the results are discussed below.

A.2.2. Data

Data

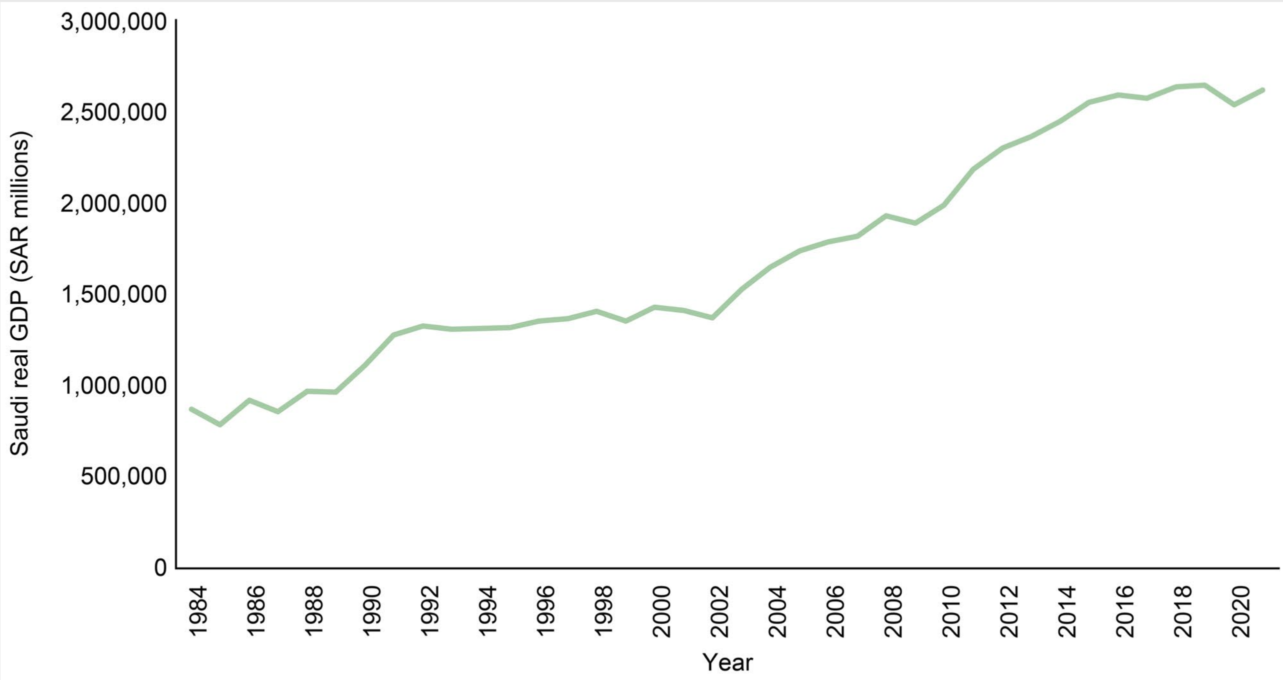
Data on total CO_2 emissions were obtained from Enerdata (2022). These data exclude emissions from land use, land use change, and forestry.



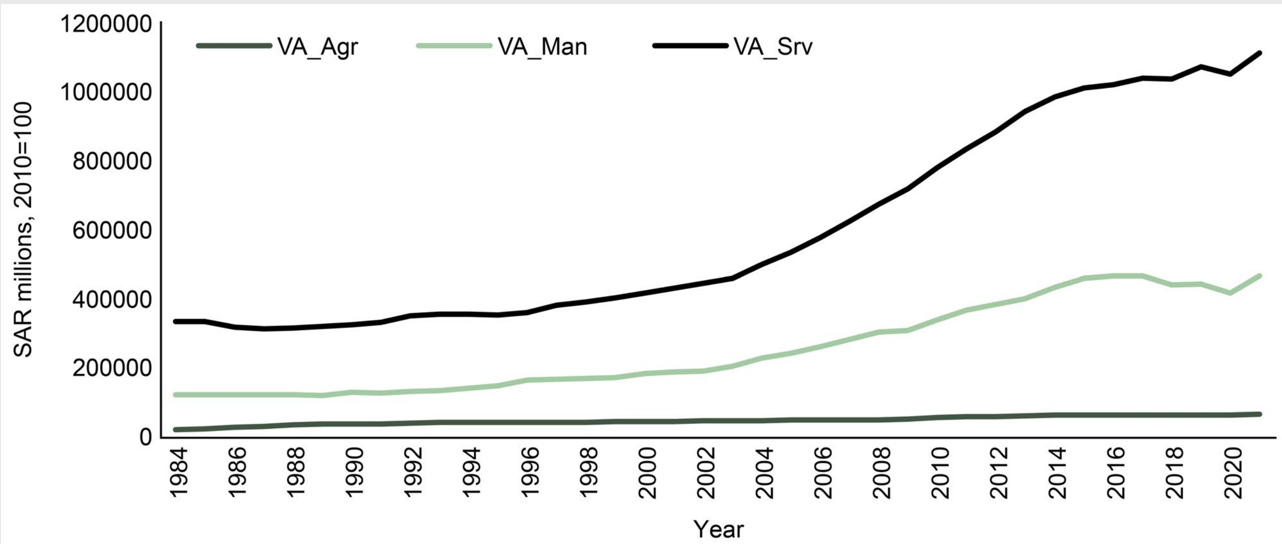
Source: Enerdata (2022).

Appendix

The real GDP data used in our estimations are obtained from the General Authority of Statistics (GASTAT) latest release from 1984–2021.



Source: Gross domestic product at constant prices, GASAT (2021) (2010=100).



Source: Gross domestic product at constant prices, GASAT (2021).

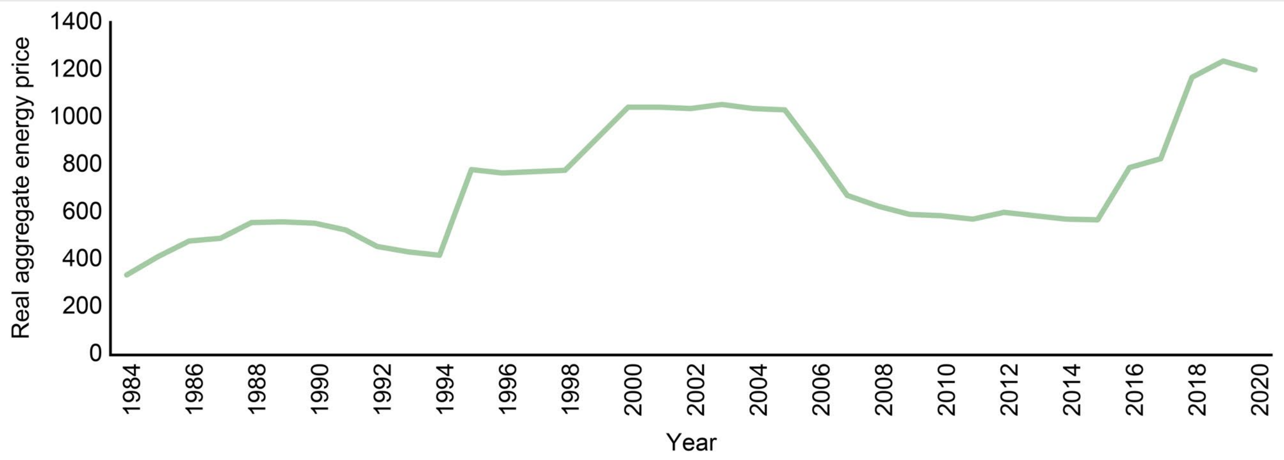
The data are comprised of nine aggregated sectoral representations of the Saudi economy. We combine these into three aggregated sectors to reduce dimensionality to compute the aggregate shares in our preferred model, and Table A1 displays our sectoral aggregation.

Table A1. Economic sector cluster.

Economic Sector Breakdown GASTAT	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 and authors' aggregation.

Our aggregate real energy index in the figure below is constructed in two steps. First, sectoral energy prices in SAR per ton of oil equivalent are obtained from Hasanov et al. (2020). Second, we construct the index 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), which is 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 is adjusted for inflation using the consumer price index (CPI), also obtained from GASTAT (2021). There are three elements influencing this index: changes in energy prices, inflation, and changes in the GDP shares of sectors. This aggregate energy price for the Saudi economy captures the average change in energy prices for the Saudi economy. Using a single average 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.



Real aggregate energy price (SAR/TOE).
Source: Hasanov et al (2020), GaSTAT, and authors' calculation.

A.3. Estimation Results

A.3.1. Overview

The overarching aim of the estimation is to find a sound statistically acceptable model that includes appropriate right-hand-side variables (or drivers) that are important in driving CO_2 emissions now and in the future. Therefore, we consider several "sets" of drivers, $\boldsymbol{X}_t$, in our initial general models that we think might produce such a preferred specification to be used to underpin the scenarios, following the estimation strategy for each set as outlined above. These sets include 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), the natural logarithm of the real energy price (p_t), and the level share of services in nonoil 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 nonoil GDP (srv_sh_t).

SET I is initially considered since GDP and the real energy price are seen as two of the most substantive drivers, and although they prove to be statistically important, in addition to the level of economic activity, the economic structure is very important in driving CO_2 emissions. Therefore, in SET II, the GDP variable is dropped and replaced in the initial general model by the value added of the manufacturing, agriculture, and service sectors. SET III at this stage further augments Step 1 with the proportionate share of services within nonoil GDP included in the general model – the idea being that if total GDP were constant, then an increase in the share of services (and implicitly a decrease in the share of manufacturing and agriculture) of nonoil GDP could potentially substantially reduce CO_2 emissions. Finally, SET IV, based on the same principle as SET III, augments Step I with the natural logarithm of the share of services within nonoil GDP instead of the actual proportion. Where applicable, the preferred models obtained with each of two econometric methodologies, Autometrics and the STSM, with the various sets of drivers, are presented and discussed below.

A.3.2. Autometrics Specifications

The estimated preferred specifications from applying the Autometrics estimation strategy outlined above to SET I and SET II only are presented in Table A1 since no acceptable specification is found for SET III and SET IV, with the services share variables being insignificant and/or having the wrong sign. Hence, consistent with the general-to-specific modeling approach, the estimations that started with SET III and SET IV result in the final model for SET 1 presented in Table A2, 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. The estimate 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.

Table A2. Summary of Autometrics estimation results (dependent variable: co_{2_t}).

	SET I	SET II	SET III	SET IV
Variable/Coefficients				
Intercepts	5.333***	-2.2140***	Given that 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 that 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.
$co_{2_{t-1}}$	-	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***		
$agrva_t$		-		
$agrva_{t-1}$		-		
$srvva_t$		-		
$srvva_{t-1}$		-		
$SRVSH\_NO_t$				
$SRVSH\_NO_{t-1}$				
$srvsh\_no_t$				
$srvsh\_no_{t-1}$				
Interventions/ Indicator	S1:1986**	T1:1987***		
	T1:1992***	S1:1990***		
	T1:1993***	S1:1993***		
	T1:2015***	T1:1996***		
		T11997***		
		I:2002***		
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		
$\overline{R}^2$	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:
*- *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively;*
- R^2 is the coefficient of determination, $\overline{R}^2$ is the adjusted coefficient of determination, F is the overall goodness-of-fit statistic distributed as $F_{(v1, v2)}$, and 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 heteroscedasticity statistics both distributed as $F_{(v1, v2)}$; and
- RESET is the Ramsey RESET statistic distributed as $F_{(v1, v2)}$.
Source: Authors' estimation results

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, which fails at the 10% significance level. The final equation for SET II, unlike that 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 variables for the other sectors are not retained since they are not statistically significant. 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.

A.3.3. STSM Specifications

The estimated preferred specifications from applying the STSM procedure to all four sets of explanatory variables are presented in Table A2. 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, suggesting that a 1% increase in the two variables would reduce CO_2 emissions by 0.10% and increase CO_2 emissions by 0.23%, respectively – a response similar to that under the Autometrics model for the real energy price for SET I but somewhat higher for GDP. The preferred model also includes a UET, illustrated at the top left of Fig. A1. This is generally upward sloping (CO_2 increasing), although the rate of increases falls toward the end of the estimation period given the inclusion of a slope intervention in 2015. At the end of the estimation period, with the real energy price and GDP held 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.

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 or 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 (as in the Autometrics model). The

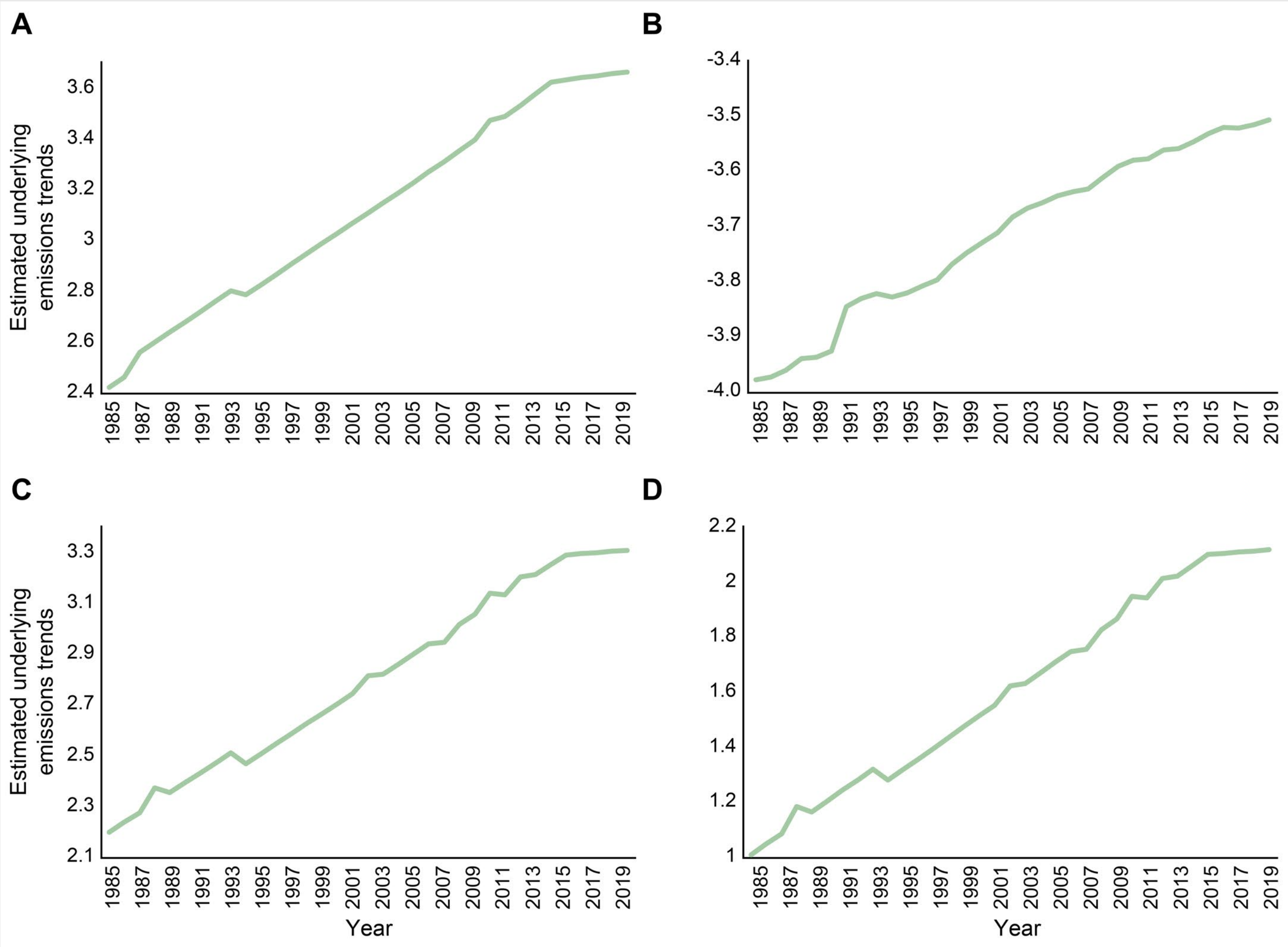
Table A3. Summary of the STSM estimation results (dependent variable: co_{2_t}).

	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***		
$agrva_{t-1}$		-		
$srvva_t$		-		
$srvva_{t-1}$		-		
$SRVSH\_NO_t$			-1.2455***	
$SRVSH\_NO_{t-1}$			-	
$srvsh\_no_t$				-0.8313***
$srvsh\_no_{t-1}$				-
Interventions:				
	Lvl1987***	Lvl1991***	Irr1988***	Irr1988***
	Lvl1994***		Lvl1994***	Lvl1994***
	Irr2010*		Irr2002**	Irr2002**
			Irr2007***	Irr2007***
			Irr2010***	Irr2010***
			Irr2012**	Irr2012**
			Slp2016***	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:
*- *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively;*
- R^2 is the coefficient of determination, R_d^2 is the coefficient of determination based on differences, and p.e.v. is the prediction error variance;
- AIC and BIC are the Akaike and Bayesian information criteria based on the p.e.v.
- Normality is the Bowman–Shenton statistics, which 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 $\chi^2_{(f)}$.
Source: Authors' estimation results

Figure A1. Estimated underlying emissions trends (UETs) for the STSM preferred specifications.



Source: Authors' estimation results.

model, therefore, suggests that a 1% increase in the real energy price would 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 – results that are somewhat different from those obtained by the Autometrics estimates for SET II. The estimated UET for the STSM estimates for SET II is illustrated in the top right of Fig. A1 and again is generally upward sloping, and at the end of the estimation period, with the real energy price, manufacturing value added, and agriculture value added held constant, the trend suggests an autonomous increase in CO_2 emissions of 1.19% per annum – somewhat larger than that under the SET 1 STSM specification.

The preferred specifications for SET III and SET IV are very similar, with the same interventions and 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 nonoil GDP is included whereas, for SET IV, it is the natural logarithm of the share of services value added in nonoil 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 Fig. A1; 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) of 3.46% per annum; thus, the only difference between the SET II and SET IV estimated models is how services value added is entered in the equations. For SET III, it is the actual proportionate share of services in nonoil GDP, and the estimated coefficient suggests that a one-percentage-point increase in this 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-point increase in the share would reduce CO_2 emissions by 0.83%.

A.3.4. Choice of 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 of 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 presented in the main text. 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.

Considering the two Autometrics specifications in Table A1, the specification for SET II has lower information criteria values but fails one of the diagnostic tests; hence, on balance, the SET I specification that includes the real energy price and GDP is preferred. Considering the four STSM specifications in Table A2, they all pass all the diagnostic tests, but the specifications for SET III and SET IV clearly have lower information criteria values than the specifications for SET I and SET II – so this would suggest that 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 criteria values and that the actual share rather than the natural log of the share is easier to interpret, it is preferred to the SET IV specification. Thus, our decision comes down to choosing between the Autometrics specification for SET I and the STSM specification for SRT III, and given the extra drivers available in the STSM specification in terms of the service value added share and the trend, the specification for SET III is chosen and used to generate the scenarios in the main text.

Notes

Notes

About the Authors

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Abdulelah is an economist and senior research associate at KAPSARC. He leads the application of behavioral economics projects to energy policymaking in Saudi Arabia. Abdulelah primarily works with econometric modeling. His research focuses on macroeconomics and energy, counterfactual analysis, international trade and investment flows, financial development, and public policy. His work has been published in leading peer-reviewed journals and has been utilized in many advisory engagements with the Saudi energy ecosystem. During the Saudi G20 presidency, he was the Think20 (T20) task force coordinator and a member of the Trade, Investment, and Growth Taskforce and a coauthor of its reports. Before joining KAPSARC, Abdulelah was an economic consultant for a major consultancy firm, where he provided policy analyses, modeling, and forecasting of the impacts of public spending on social and economic indicators.

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Anwar A. Gasim is an energy and environmental economist with a strong engineering background. He leads a cross-functional team on the project titled "Modeling Energy Demand, Emissions, and the Impacts of Energy Price Reform." This project includes studies on elasticities, emissions forecasting, the economic and environmental impacts of reforms, and the determinants of successful energy policy outcomes. He is also involved in multiple studies on carbon markets. Anwar's research has been published in leading journals and has been picked up by numerous media publications, such as the Saudi Gazette and Arab News. His work has supported key advisory engagements with the Saudi energy sector.

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About the Project

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

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

The first area focuses on advisory and applied research activities around modeling indicators of energy consumption. Applying econometric techniques and tools to time series data on targeted indicators will enable the project to reveal relation-specific parameters, their features over time, and forecast values for the expected or designed scenarios.

The second area models the environmental impacts of energy consumption, employing econometric techniques and tools to the relevant framework and data to make policy simulations and forecasts. Considering the ongoing activities in the Kingdom to control and mitigate the adverse impacts of energy consumption, this area will contribute to policymaking by providing a clear picture of the channels and trajectories of these adverse impacts.

The third area will analyze the trajectories and potential of energy efficiency at the sectoral and regional levels. This will reveal historical efficiency trends, potentials, and channels to make and increase energy consumption efficiency.

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