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Baseline Forecasts of Carbon Dioxide Emissions for Saudi Arabia Using the Structural Time Series Model and Autometrics

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Key Points

As a party to the Paris Agreement, Saudi Arabia submitted a baseline emissions reduction target as part of its nationally determined contribution. The baseline target rests on the development of a baseline emissions scenario. This is a counterfactual scenario that shows how emissions would evolve without any further efforts to reduce emissions. Saudi Arabia's quantitative baseline scenario is not yet publicly available.

We use two different econometric methods within a univariate framework to generate baseline emissions forecasts for Saudi Arabia. We extend current drivers, trends and policies into the future without making assumptions about certain factors, such as economic growth, in the coming decades. Using two different methods provides a robustness check, as each method has strengths and weaknesses.

The two methods' baseline projections of Saudi Arabia's total carbon dioxide (CO2) emissions are consistent. Averaged together, they suggest that Saudi Arabia's total CO2 emissions will increase from 540 million tonnes (Mt) in 2019 to 651 Mt by 2030. These emissions will rise to 944 Mt by 2060. Our projections are based on the assumption that current trends, drivers and policies in 2019 are extended into the future. In other words, we assume that no further policies to curb emissions are undertaken. The confidence intervals for the 2030 projections are narrow, whereas those for the 2060 projections. are very wide. This result reflects the high amount of uncertainty associated with long-term projections. targets that might be beyond the reach of current technologies. However, technological advancements could make this ambition achievable by 2040 or 2050.

Summary

To tackle the threat of climate change, countries worldwide have signed the Paris Agreement. This agreement aims to limit the global average temperature increase to below 2 degrees Celsius and potentially below 1.5 degrees Celsius above pre-industrial levels (UNFCCC 2015). Parties to the Paris Agreement are required to submit domestic climate plans detailing their mitigation measures, known as nationally determined contributions (NDCs). These plans detail countries' ambitions and efforts to combat and respond to climate change. NDCs are communicated at five-year intervals, and each successive NDC must represent an increase in ambition over the previous one.

As a developing country party to the Paris Agreement, Saudi Arabia made its first NDC submission in 2015. At that time, the Kingdom submitted a greenhouse gas (GHG) emissions avoidance target of 130 million tonnes (Mt) of carbon dioxide (CO_2) equivalent. This total emissions reduction target includes CO_2 emission reductions, among other GHGs. Saudi Arabia updated its NDC in 2021. It set a new, more ambitious target of reducing, avoiding and removing 278 Mt of CO_2 equivalent emissions annually by 2030.

Saudi Arabia set its NDC target relative to a baseline emissions scenario. Such targets are commonly referred to as 'baseline targets,' and most developing countries have adopted such targets. Baseline targets require a baseline scenario; that is, a counterfactual projection that describes the evolution of emissions without any additional policy efforts. In the baseline scenario, the current underlying policies and drivers remain unchanged in the future. The Intergovernmental Panel on Climate Change (IPCC 2022) defines a baseline scenario as being "based on 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." Saudi Arabia's NDC does not include quantitative information about its baseline scenario.

Developing baselines can be challenging, as projections can be sensitive to methods, assumptions and many other factors (e.g., financial crises and the COVID-19 pandemic). Methods for modeling and forecasting emissions involve trade-offs. Statistical methods use historical time series data to produce a mathematical relationship that can be used to generate baseline emissions forecasts. In a univariate framework, statistical methods are used to model and forecast a single variable, such as total CO_2 emissions. In a multivariate framework, additional explanatory variables, such as gross domestic product (GDP), are included in the statistical equation. Although multivariate models may be more relevant for policy simulation projections, univariate models do not require any assumptions about the underlying drivers like GDP. Instead, univariate models are inherently based on the assumption that current trends, policies and drivers extend into the future, thereby creating a natural baseline projection.

We estimate univariate models for the same data and estimation period using two methods: autometrics and the structural time series model. After estimating statistically acceptable equations through these methods, we use them to generate

forecasts of Saudi Arabia's baseline CO2 emissions. We focus exclusively on modeling CO2 emissions, which account for the largest share of Saudi Arabia's GHG emissions. Our projections are found to be consistent, indicating their robustness. We therefore average the two projections together to determine a baseline scenario for Saudi Arabia's CO2 emissions.

Our average baseline projection suggests that Saudi Arabia's CO2 emissions will grow from 540 Mt in 2019 to 651 Mt in 2030. This projection is based on the assumption that trends, drivers and policies in 2019 continue and no additional measures to curb emissions are undertaken. In its updated NDC, Saudi Arabia set a target of reducing, avoiding and removing 278 Mt of CO2 equivalent GHG emissions annually by 2030 (Kingdom of Saudi Arabia 2021). Thus, our baseline projection suggests that the Kingdom would be aiming at an absolute CO2 emissions level of about 429 Mt in 2030 if we convert its NDC baseline target using our quantitative baseline and assume that its CO2 reductions account for 80% of the total GHG emission reduction needed to achieve its NDC target.

Our average baseline projection also reveals that Saudi Arabia's CO2 emissions will grow to 941 Mt by 2060. This projection is again based on the assumption that the trends, drivers and policies in 2019 remain the same over time. This assumption is unlikely to hold because in 2021, Saudi Arabia set a goal to achieve net-zero emissions by 2060. Moreover, the confidence intervals of our projections for 2060 are very wide, reflecting the high uncertainty associated with long-term forecasts, as our methods are more accurate for short- to medium-term forecasts. Nevertheless, our baseline projection to 2060 provides an indication of the policy efforts required for Saudi Arabia to fulfill its pledge of net-zero emissions in 2060.

Introduction

To tackle the threat of climate change, countries worldwide have signed the Paris Agreement. This agreement aims to limit the global average temperature increase to below 2 degrees and potentially below 1.5 degrees Celsius above pre-industrial levels (UNFCCC 2015). Parties to the Paris Agreement are required to submit domestic climate plans detailing their mitigation measures, known as nationally determined contributions (NDCs). These plans reflect their ambitions and efforts to combat and respond to climate change. NDCs are communicated at five-year intervals, and each must represent an improvement in ambition over the previous one.

As a party to the Paris Agreement, Saudi Arabia submitted an NDC in 2015. It set a target for reducing the country's greenhouse gas (GHG) emissions, including carbon dioxide (CO2) emissions. Specifically, Saudi Arabia aims to reduce its emissions by up to 130 million tonnes (Mt) of CO2 equivalent annually by 2030 (Kingdom of Saudi Arabia 2015, 1). The Kingdom submitted an updated NDC with a more ambitious target in 2021. It set a revised goal of "reducing, avoiding, and removing GHG emissions by 278 Mt [of CO2 equivalent] annually by 2030" (Kingdom of Saudi Arabia 2021, 2).

Saudi Arabia set its emissions targets relative to a baseline. Such targets are commonly referred to as 'baseline targets' (Vaidyula and Hood 2018). A baseline is based on historical data and describes the likely evolution of a country's emissions without any additional policy efforts. Thus, it acts as a reference projection for emissions. In the baseline, the underlying drivers continue to evolve in the future as they did in the past. The Intergovernmental Panel on Climate Change (IPCC 2022) defines a baseline scenario as being "based on 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." It explains 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." Most developing countries have adopted baseline targets, but the 2021 NDC updates suggest that some countries are moving toward absolute targets (Fransen 2021; UNFCCC 2021).

Providing a transparent quantitative baseline can support domestic climate policymaking. It also sends crucial signals to various actors regarding the current emissions trajectory, enabling the development of well-informed policies and interventions. Moreover, parties to the Paris Agreement are expected to provide the necessary information for clarity, transparency and understanding when communicating their NDCs (UN 2015). Although Saudi Arabia's NDC provides a lot of qualitative information about its dynamic baselines and the key underlying drivers, it does not provide quantitative baseline projections.

Developing quantitative baseline projections can be challenging, as Vaidyula and Hood (2018) explain. Multiple variables, such as the policies that are included in baseline projections, can potentially affect a country's emissions trajectory. Similarly, assumptions about energy prices and economic growth also affect the evolution of baseline emissions. Furthermore, the start date for the baseline can affect the projected evolution of a country's emissions. Different methodologies also produce different baselines even when the same data and time periods are used.

Choosing a methodology for modeling and forecasting emissions involves making trade-offs, as each method has strengths and weaknesses. Statistical forecasting methods estimate models based on historical time series data and use those models to generate forecasts. Statistical methods within a univariate framework focus on modeling and forecasting a single variable, such as total CO2 emissions. By contrast, multivariate frameworks include explanatory variables, such as energy prices and gross domestic product (GDP), as drivers in the equation. Multivariate models may be more relevant for policy simulations (see, for example, Clements and Hendry [1998]; Hendry [2018]). However, univariate models eliminate the need to make assumptions or forecast the evolution of energy prices or GDP. Instead, univariate forecasts implicitly extend current trends, policies and drivers into the future, thereby creating a natural baseline scenario (Belbute and Pereira 2020). (The appendix provides a review of some prior studies that use different econometric methods to forecast CO2 emissions.)

This study provides information about the potential evolution of Saudi Arabia's baseline emissions through 2030 and up to 2060 by developing baseline emission projections. Our analysis focuses solely on CO2 emissions, which account for about 80% to 90% of Saudi Arabia's total GHG emissions according to multiple sources (ClimateWatch 2022). We generate baseline CO2 projections using two different univariate econometric methods: autometrics and the structural time series model (STSM). We use these two methods because they can explain the data using a combination of trends and interventions. Furthermore, both methods explain the data in different ways, providing a robustness check on the estimated models and projections.

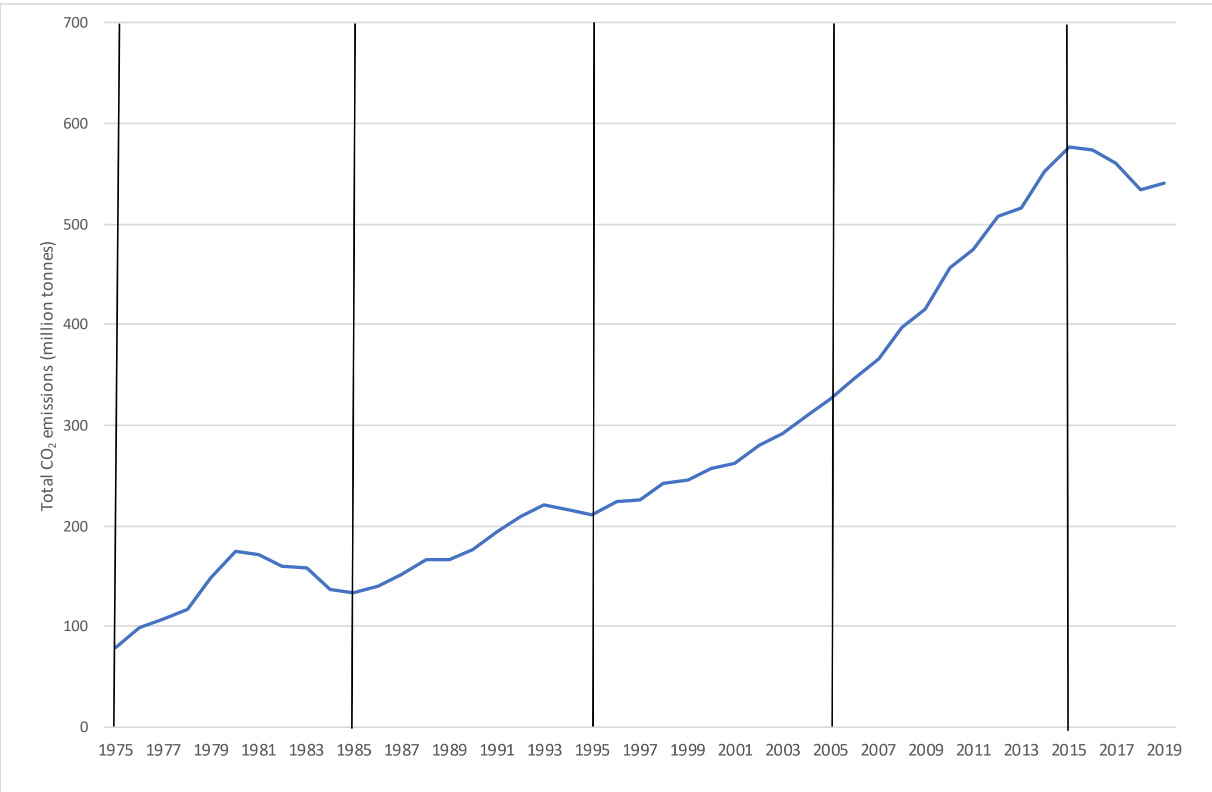
The two methods generate baseline forecasts that appear consistent, indicating their robustness. Our average baseline forecast suggests that Saudi Arabia's CO2 emissions will grow from 540 Mt in 2019 to 651 Mt by 2030. By 2060, baseline CO2 emissions are projected to grow to 944 Mt, although the confidence intervals for this estimate become very wide.

Background

Saudi Arabia's CO_2 emissions have grown rapidly over the past several decades (Enerdata 2022). Figure 1 illustrates the evolution of its CO_2 emissions excluding land use and forestry, which constitute only a small emissions sink in the Kingdom. The figure reveals a generally upward sloping trend, although emissions have grown at different speeds in different periods. Between 1975 and 1985, CO_2 emissions grew on average by 5.4% a year, rising from 79 Mt to 134 Mt. During the following two decades (1985-1995 and 1995-2005), the growth in CO_2 emissions was slightly slower. The average annual growth rates in these decades were 4.6% and 4.5%, respectively. Between 2006 and 2015, growth accelerated to 5.8% per year, causing CO_2 emissions to reach a peak of 576 Mt in 2015. However, starting in 2015, CO_2 emissions began falling at an average rate of -1.6% per year, reaching about 540 Mt by 2019.

Many factors have contributed to the recent decline in Saudi Arabia's CO_2 emissions. In 2016, the Saudi government launched Saudi Vision 2030 (Kingdom of Saudi Arabia 2016), a blueprint for economic and social reform. Vision 2030 encompasses many programs, each of which includes numerous initiatives. Some of the initiatives that were launched include energy price reforms, the introduction of a value-added tax (VAT) and levies on expatriates. Saudi Vision 2030 also encompasses initiatives

Figure 1. Saudi Arabia's total CO_2 emissions (excluding land use, land use change and forestry).



Source: Enerdata 2022.

that have increased women's participation in the workforce, diversified the Saudi economy and encouraged the renewable energy sector's development. All of these initiatives likely played a role in Saudi Arabia's recent declines in emissions.

CO_2 emissions from fuel combustion currently account for over 90% of total CO_2 emissions (Enerdata, 2022). Thus, factors that reduce energy consumption, such as higher energy prices and energy efficiency improvements, have likely contributed to the decline in CO_2 emissions. Aldubyan and Gasim (2021) quantify the contributions of energy price reforms in 2016 and 2018 to reductions in Saudi Arabia's gasoline and residential electricity consumption. Mikayilov et al. (2020) assess these reforms' effects on regional electricity consumption. Both studies show that energy efficiency improvements contributed significantly to the decrease in residential electricity consumption. Multiple energy efficiency programs in Saudi Arabia, especially following the establishment of the Saudi Energy Efficiency Center (SEEC) in 2010, have led to emissions-reducing energy efficiency improvements. For example, Saudi Arabia increased its minimum energy efficiency standards for air conditioners (SEEC 2022).

Saudi Arabia's CO_2 emissions trended upward for most of the period from 1975 to 2019 but have trended downward over the last five years. Thus, projecting Saudi Arabia's total CO_2 emissions in the future is challenging. One possible approach is to extend the average growth rate of 4.5% over the entire period into the future. This method implies that CO_2 emissions will rise from 540 Mt in 2019 to 3,239 Mt by 2060. An alternative approach is to extend the average growth rate over the period from 2015 to 2019, which is -1.6%. With this method, CO_2 emissions are projected to fall to 279 Mt by 2060. These predictions are clearly very divergent. Thus, to address some of these challenges, we employ advanced statistical methods to forecast baseline CO_2 emissions.

The data period that we use for our forecasts ends in 2019. In 2020, Saudi Arabia's CO_2 emissions from fuel combustion declined by 3.3%, the second largest drop after 2018. This decline was likely primarily due to the unprecedented impact of the COVID-19 pandemic (Al Shehri et al. 2021) and an increase in VAT. We use data through 2019 for our projections because of the pandemic's unprecedented effects and because it is the baseline year for Saudi Arabia's NDC.

Methodologies and Data

Overview of Methodologies

Many methods can be used to produce baseline CO2 emissions forecasts. However, to the best of our knowledge, neither the STSM nor the autometrics method has been used to forecast baseline CO2 emissions. These methods are used extensively for other types of forecasting. We use these two methods because they can explain the data with a combination of trends and interventions. These interventions can capture the effects of shocks and policy changes on total CO2 emissions, and their omission can lead to biased estimation results. Although both STSMs and autometrics capture interventions, they do so in different ways. Thus, using two methods provides a natural robustness check for the baseline forecasts.

To ensure that the two approaches result in comparable models, we start the estimation procedure with the same general univariate model. In both approaches, we model the natural logarithm of total CO2 emissions, denoted by ${co_2}_t$, where t denotes the year. We include four lags of the dependent variable to capture autoregressive behavior in the equations. We choose four lags to balance the need for a reasonable number of lags in a univariate model with the number of observations. This reasoning is consistent with Enders (2015). We use data from 1984 to 2019 in the estimation. The general specification used as a starting point for both methods is as follows:

$$\begin{aligned} {co_2}_t &= intercept + \alpha_1 {co_2}_{t-1} + \alpha_2 {co_2}_{t-2} + \alpha_3 {co_2}_{t-3} \\ &\quad + \alpha_4 {co_2}_{t-4} + random\ error\ term. \qquad (1) \end{aligned}$$

We can obtain a specific preferred or final equation from this general starting point. We add statistically significant interventions (i.e., dummy variables) to Eq. (1) and drop statistically insignificant right-hand side variables, until we arrive at a specific final parsimonious model, one that passes an array of diagnostic tests. This approach is commonly known as the general-to-specific approach. The appendix provides more details on the methodologies, data and chosen estimation period.

Data

We obtain time series data on emissions for Saudi Arabia from Enerdata (2022). We model total CO2 emissions, excluding those associated with land use, land use change and forestry (LULUCF). Total CO2 emissions are the sum of emissions from several sources, such as fuel combustion, industrial processes, agriculture and fugitive emissions (excluding LULUCF emissions). The CO2 produced by fuel combustion accounts for most of the total, with industrial processes accounting for most of the remainder. From 1975 to 1983, the share of fuel combustion emissions in Saudi Arabia's total CO2 emissions grew rapidly from 28% to 89%. Since then, fuel combustion has accounted for over 90% of Saudi Arabia’s CO2 emissions. The establishment of Saudi Arabia’s Master Gas System may have been partly responsible for this growth. This system is a network of facilities and pipelines for capturing, processing and transporting gas for industrial use (Al-Suwailem 2020).

To minimize data-related issues that may affect the econometric estimation, we used 1984 to 2019 as our estimation period. During this period, the shares of emissions across different subsectors appear to be relatively stable. Although preliminary CO2 emissions data are available for 2020, we end the estimation period in 2019 because of the unprecedented impact of the COVID-19 pandemic. An estimated equation that ends in such an abnormal year may lead to distorted long-term projections (Clements and Hendry 1998). Moreover, the base year for the updated Saudi NDC is 2019.

Econometric Results and Baseline Forecasts

Preferred Model with the Autometrics Approach

The final preferred model estimated over the period from 1984 to 2019 using the autometrics approach is as follows:

$$\widehat{co_2}_t = 0.1421^{*} + 1.2878^{***} co_{2_{t-1}} - 0.3079^{**} co_{2_{t-2}} - 0.1857^{***} IIS_{1984} \qquad (2)$$

where $\hat{\square}$ denotes a fitted (estimated) value. $\square^{*}$, $\square^{**}$ and $\square^{***}$ indicate coefficients that are statistically significant at the 10%, 5% and 1% levels, respectively. Eq. (2) includes two significant lagged dependent variables: the one-year and two-year lags of the natural logarithm of CO2 emissions. The coefficient of the one-year lag is positive and greater than one, and the coefficient of the two-year lag is negative and smaller in absolute terms. These variables' positive combined effect is slightly less than one. This combined effect suggests continued growth in future emissions, as is expected to occur in developing countries such as Saudi Arabia. Only one impulse indicator (IIS_{1984}) is retained in the model following the autometric selection procedure. The full details of the estimation of Eq. (2) are provided in the appendix.

Preferred Model with the STSM Approach

The final preferred model estimated over the period from 1984 to 2019 using the STSM approach is as follows:

$$\widehat{co_2}_t = \hat{\gamma}_t + 0.5803^{***} co_{2_{t-1}} - 0.6591^{***} co_{3_{t-3}}. \qquad (3.1)$$

The estimated trend ($\hat{\gamma}_t$) is given by

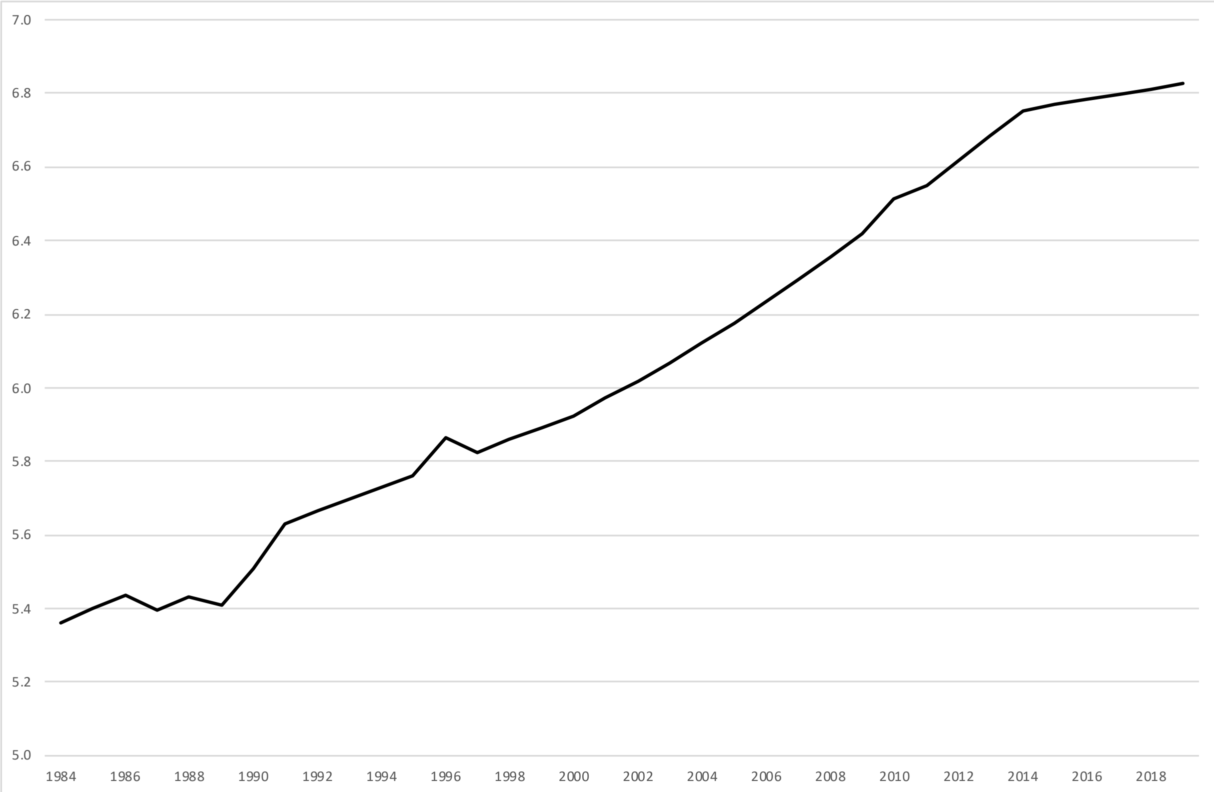
$$\hat{\gamma}_t = \hat{\mu}_t - 0.0787^{***} Lvl_{1987} - 0.0638^{***} Irr_{1989} + 0.0882^{***} Lvl_{1991} + 0.0711^{***} Irr_{1996} + 0.0163^{*} Slp_{2001} + 0.0300^{**} Irr_{2010} - 0.0525^{***} Slp_{2015}. \qquad (3.2)$$

Again, $\square^{*}$, $\square^{**}$ and $\square^{***}$ represent statistically significant coefficients at the 10%, 5% and 1% levels, respectively. $\hat{\mu}_t$ represents the estimated level component of the trend. The appendix provides more details.

The estimated STSM coefficients in Eq. (3.1) include one-year and three-year lags of the natural logarithm of CO2 emissions. The coefficient of the one-year lag is positive. The coefficient of the three-year lag is negative and slightly larger than the coefficient of the one-year lag in absolute terms. Thus, the combined coefficients have a negative effect, although small (about -0.07). This overall negative effect suggests a slight decrease in future emissions.

The estimated trend given by Eq. (3.2) is clearly upward-sloping, as Figure 2 shows. This trend therefore offsets the small negative effect of the estimated coefficients, and the emissions projections are ultimately upward-sloping. The estimated trend includes several interventions. The level intervention in 1991 (Lvl_{1991}) reflects the Gulf War, and the irregular intervention in 1996 (Irr_{1996}) reflects various energy price increases. Finally, the slope intervention in 2015 (Slp_{2015}) likely reflects Saudi Arabia's economic reforms through Saudi Vision 2030.

Figure 2. Estimated trend (γ) from the STSM preferred specification.



Source: Authors' calculations.

Baseline Forecasts

We use the preferred autometrics and STSM specifications to forecast baseline total CO2 emissions through 2060 for Saudi Arabia. The projections are generally consistent, revealing that total CO2 emissions will continue to grow in the future. However, our projections suggest that they will grow at a relatively slower rate than they did throughout most of 1984 to 2019.

Autometrics Baseline Forecasts

We can easily generate projections using the preferred autometrics specification because it includes only one impulse indicator, for 1984. This projection is therefore based only on the past values of the natural logarithm of Saudi Arabia's lagged one- and two-year CO2 emissions. The baseline projection generated using autometrics is upward-sloping owing to the combined positive coefficients of the lagged terms. The baseline forecasts are presented in Table 1 and Figure 3a. Figure 3a also shows the 95% confidence intervals for the autometrics projections. The confidence intervals using autometrics are initially narrow but increase as the projections approach 2060. For the baseline forecast estimate of 671 Mt in 2030, the lower bound is 506 Mt, and the upper bound is 890 Mt. For the 2060 baseline forecast estimate of 941 Mt, the lower bound is 631 Mt, and the upper bound is 1,403 Mt. This wide interval in 2060 reflects the high level of uncertainty associated with long-term projections.

STSM Baseline Forecasts

With a conventional deterministic trend model, a projection is simply a linear extension of the current trend over the estimation period. However, with the STSM approach, the estimated trend is often found to be stochastic rather than deterministic and is therefore nonlinear, as in this case. We find that the estimated trend makes a nontrivial contribution to the fitted model over the sample period. Thus, it also contributes considerably to the future projections. We generate the baseline forecast using the one- and three-year lags of the natural logarithm of Saudi Arabia's CO2 emissions and the projected trend. This baseline projection is upward-sloping with some minor cyclical behavior around its level. Cycles are three to four years long. We want to focus on long-term projections rather than minor cyclical fluctuations, so we use a seven-year moving average to smooth the STSM projections. Table 1 and Figure 3b present these projections alongside the autometrics projections.

Figure 3b also shows the 95% confidence intervals for the STSM projections. These confidence intervals are initially narrow but grow much larger toward 2060. For the baseline forecast estimate of 632 Mt in 2030, the lower bound is 538 Mt, and the upper bound is 743 Mt. The confidence interval for this short-term projection is narrower than that obtained using the autometrics approach. However, the autometrics approach provides narrow confidence intervals for the long-term projections. Specifically, the STSM approach produces smaller standard errors through 2033, whereas autometrics produces smaller standard errors from 2034 onward.

This finding regarding the confidence intervals may be another argument for averaging the projections. The wider long-term confidence intervals for the STSM approach are likely driven by its stochastic trend. This trend helps to better explain the data but also introduces additional sources of uncertainty to the long-term projections. For example, STSM's 2060 baseline emissions forecast is 947 Mt. The corresponding confidence interval has a lower bound of 300 Mt and an upper bound of 2,997 Mt. This interval is considerably wider than that for the autometrics baseline projection.

Average Baseline Forecasts

Table 1 and Figure 3 show that both methods produce similar long-term projections. By 2030, both projections suggest that Saudi Arabia will emit between 600 Mt and 700 Mt of CO2 in a baseline scenario. By 2060, baseline emissions will reach almost 1,000 Mt. The methods use different approaches for the trends and interventions, and their preferred specifications include different lagged dependent variables. Nevertheless, they deliver similar baseline projections. We set the average of both forecasts as our baseline scenario for Saudi Arabia's CO2 emissions. Combining the two forecasts provides an insurance policy on the forecasted values (e.g., Castle, Clements, and Hendry [2019]; Castle, Doornik, and Hendry [2021]), thereby potentially producing a more accurate baseline projection. This baseline scenario is illustrated in Figure 3c.

Impact of the COVID-19 Pandemic

As previously mentioned, preliminary data suggest that CO2 emissions decreased in 2020 during the COVID-19 pandemic. It is possible to adjust the short-term forecasts using the intercept correction approach as new data become available (e.g., Clements and Hendry 1998). Nonetheless, the COVID-19 pandemic is likely to be a short-term shock and to have a relatively limited impact on the medium- to longer-term projections.

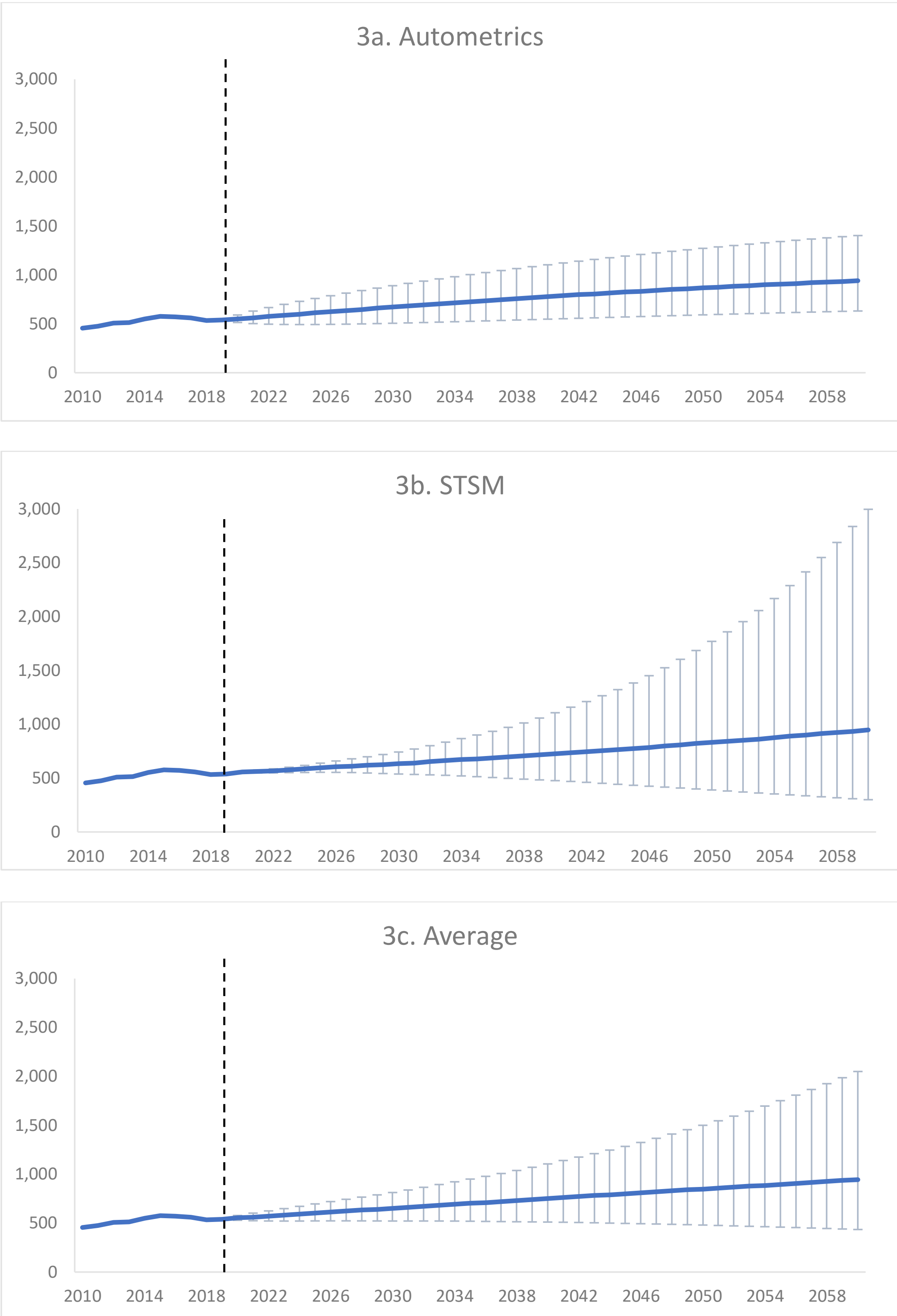
Table 1. Saudi Arabia's total CO_2 emissions (in Mt).

Year	Autometrics	STSM	Average
1984	136.2	136.2	136.2
1990	176.5	176.5	176.5
2000	257.3	257.3	257.3
2010	455.7	455.7	455.7
2019	540.4	540.4	540.4
2025	611.8	595.1	603.4
2030	670.8	632.2	651.2
2035	726.1	680.1	702.8
2040	777.5	726.5	751.6
2050	867.5	831.0	849.0
2060	940.9	947.9	944.4

Source: Authors' calculations.

Note: Values reflect historical data up to 2019 and projections thereafter.

Figure 3. Saudi Arabia's total historical CO2 emissions (2010-2019) and projections (2020-2060) in Mt.



Source: Authors' calculations.

Conclusion and Policy Implications

Saudi Arabia, like many other countries, set a baseline emissions target in its NDC to mitigate climate change. Baseline targets are developed by constructing baseline scenarios. Thus, understanding the evolution of Saudi Arabia's baseline emissions is vital for understanding its emissions target. However, Saudi Arabia's NDC does not include quantitative information about its baseline. Providing a quantitative baseline can support domestic climate policymaking and send crucial signals to various actors about the country's future emissions trajectory, which is critical for developing well-informed policies and interventions. Moreover, parties to the Paris Agreement are required to provide the information necessary for clarity, transparency and understanding when communicating their NDCs (U.N. 2015).

This study therefore helps to inform climate policymaking by projecting Saudi Arabia's baseline CO2 emissions. We use two different econometric methods: the STSM and autometrics. We present emissions projections through 2030 and until 2060 along with insights about the level of uncertainty of these projections. We estimate our models using the same data and estimation period for both methods. We then use these estimated models to generate forecasts of Saudi Arabia's baseline CO2 emissions. We find that both methods' projections based on the preferred models are consistent, indicating their robustness. We set the average of both projections as the baseline forecast for Saudi Arabia's CO2 emissions. As mentioned above, the baseline projection is not a prediction of the future but rather a projection of emissions if no further policy efforts are made.

According to our projection, Saudi Arabia's CO2 emissions will grow from 540 Mt in 2019 to 651 Mt by 2030 in the baseline scenario. This scenario assumes that the trends, drivers and policies in 2019 continue into the future. We use 2019 as the base year for our projections, as it is the base year for Saudi Arabia's current NDC. In its updated NDC, Saudi Arabia set a target to reduce and avoid 278 Mt of CO2 equivalent GHG emissions annually by 2030 (Kingdom of Saudi Arabia 2021). If our 2030 projection is the baseline, then the Kingdom aims to achieve absolute CO2 emissions of about 429 Mt by 2030. This estimate is based on the assumption that 80% of the NDC GHG emissions reduction is achieved through CO2 emission reductions. As noted in its NDC, Saudi Arabia expects to achieve its 2030 target through energy efficiency improvements and renewable energy installation, among many other programs and initiatives. Renewable energy is expected to account for 50% of the power generation mix by 2030. Saudi Arabia also plans to install carbon capture, utilization and storage capacity and displace more carbon-intensive fuels with natural gas.

Our baseline projection suggests that Saudi Arabia's CO2 emissions will increase to 944 Mt by 2060. This outcome is unlikely. Nevertheless, this projection demonstrates the magnitude of the additional policy efforts required for Saudi Arabia to achieve net-zero emissions by 2060, as it has pledged (Arab News 2021). Moreover, the confidence intervals for our long-term projections (e.g., through 2060) are very wide. Thus, these baseline projections are more appropriate for setting nearer-term targets (e.g., Saudi Arabia's NDC). A key advantage of using econometric methods for generating projections is that they clearly show the error bars associated with the projections. It can be much more challenging to generate such error bars using other modeling approaches, meaning that they are often left out of the projections.

Conclusion and Policy Implications

Saudi Arabia is currently undergoing rapid social and economic reforms through Saudi Vision 2030 (Kingdom of Saudi Arabia 2016). These changes add further complexity when projecting baseline CO2 emissions. Saudi Arabia's emissions grew rapidly between the 1980s and 2015, when they started declining following reforms. The rapid pace of change and reform in Saudi Arabia is expected to continue over the coming years (Kingdom of Saudi Arabia 2016). Thus, baseline forecasting for Saudi Arabia will continue to be challenging. Saudi Arabia's updated NDC describes two different baseline scenarios, referred to as 'dynamic baselines' due to the difficulties developing a single baseline scenario for Saudi Arabia.

In summary, this study provides a robust baseline projection for Saudi Arabia's CO2 emissions. We project that they will rise to 651 Mt by 2030, the target year of Saudi Arabia's NDC, in a baseline scenario. They will increase to 944 Mt by 2060, the year in which Saudi Arabia aims to achieve net-zero emissions. These projections highlight the magnitude of the efforts needed for Saudi Arabia to achieve its targets and fulfill its pledges. Nevertheless, the rapid pace of change and reform in Saudi Arabia may alter the evolution of its baseline CO2 emissions. Given the economic transformation occurring in the country, future research can build on these univariate projections by adding explanatory variables to the econometric equations. These multivariate models can also explore the influences of different policy scenarios on the evolution of Saudi Arabia's emissions. Future research can also extend this analysis to other important GHGs, such as methane.

Appendix

A.1. Literature Review

The pressure to tackle climate change is rising, and the importance of understanding the future evolution of carbon dioxide (CO2) emissions is growing. Thus, the literature on modeling and forecasting CO2 emissions for a country or group of countries is vast. Shahbaz and Sinha (2019) and Mitić, Kresoja, and Minović (2019) provide recent summaries of research in this area. Given the recent nationally determined contribution (NDC) commitments, an increasing number of studies on CO2 emissions include projections. In this section, we review some of the most recent studies that include projections and CO2 emission models utilizing various econometric techniques.

Belbute and Pereira (2020) employ the autoregressive fractionally integrated moving average approach to model CO2 emissions in Portugal. They produce baseline projections up to 2050 and use them to assess the feasibility of Portugal's 2050 carbon neutrality target. They conclude that "additional policy efforts are necessary" (Belbute and Pereira 2020, 7). Hendry (2020) models CO2 emissions for the United Kingdom (U.K.). He applies a multipath machine learning search algorithm to general-to-specific modeling using data spanning from 1860 to 2017. The U.K. set a target to reduce its CO2 emissions by 80% compared with 1970 levels by 2050. Hendry (2020) concludes that large reductions in all CO2 sources will be required for the U.K. to meet that target.

Hosseini et al. (2019) examine the viability of Iran's commitment to reduce its CO2 emissions by 4% by 2030. They model the country's CO2 emissions and project that it is unlikely to meet its commitment to the Paris Agreement under business-as-usual assumptions. However, if it had fully implemented its ambitious Sixth Development Plan, it would have met its 4% reduction target as early as 2018. Xie et al. (2021) use a fractional nonlinear grey Bernoulli model to forecast China's fuel-based CO2 emissions in 2023. Their projection of 10,039 million tonnes (Mt) is slightly larger than the 9,921 Mt of emissions in 2019, the forecast base year.

To the best of our knowledge, Köne and Büke (2010) and Alshammari (2020) are the only studies to have forecast Saudi Arabia's CO2 emissions. Köne and Büke (2010) model CO2 emissions for the top 25 emitters, including Saudi Arabia, using a simple linear trend analysis. They consider low, reference and high economic growth scenarios. Although the study is dated, they forecast CO2 emissions for Saudi Arabia ranging from 496 Mt to 571 Mt in 2030. Alshammari (2020) assesses different technology options and the potential for achieving climate targets through Saudi Arabia's circular carbon economy framework. They project CO2 emissions until 2050 with different technologies. In the business-as-usual scenario, Alshammari's (2020) projected emissions for 2030 and 2050 are 643 Mt and 2,156 Mt, respectively.

An online tool, the Energy Policy Simulator (EPS; KAPSARC 2022), enables estimations of CO2 emissions by 2050 in business-as-usual and other policy scenarios. The EPS projects that Saudi Arabia's CO2 emissions will be 1,102 Mt in 2050. Additionally, the Climate Action Tracker (2022) assesses targets and ongoing policies. It provides projections up to 2030 for Saudi Arabia's CO2 emissions in different scenarios. However, the underlying model is not shared. Its projections suggest that Saudi Arabia's CO2 emissions will increase in the next few years and stabilize after 2025. Its assessment is based on a global economic efficiency perspective, which considers different ranges of average global temperature increases. Hence, it does not provide insights into the baseline trajectory of CO2 emissions.

This brief review shows that several different techniques can be used to produce baseline forecasts of CO2 emissions. Only two previous studies, those of Köne and Büke (2010) and Alshammari (2020), examine Saudi Arabia. The former of the two studies is now dated. Our study therefore contributes to the literature in two ways. First, it uses different econometric techniques from those used in the past to project emissions, as explained in the next section. Second, it applies these techniques to Saudi Arabian data to produce an updated baseline forecast through 2060. This end year is consistent with the government's recent pledge to achieve net-zero carbon emissions by 2060 (Mahdi 2021).

A.2. Methodologies

A.2.1. Autometrics

This method applies the autometrics multipath-search machine-learning algorithm (e.g., Doornik and Hendry [2018]) to the general-to-specific modeling approach (e.g., Hendry and Doornik [2014]). The autometrics algorithm identifies potential interventions caused by policy changes and shocks whose omission may lead to biased estimation results. It automatically assigns one-time pulse, blip, change-in-level and break-in-trend dummy variables to each observation. It then chooses the significant dummy variables by utilizing the block-search algorithm.

With the autometrics method, we use the following general specification to model the natural logarithm of total CO2 emissions:

$$co_{2_t} = \alpha_0 + \alpha_1 co_{2_{t-1}} + \alpha_2 co_{2_{t-2}} + \alpha_3 co_{2_{t-3}} + \alpha_4 co_{2_{t-4}} + \sum_1^T \vartheta_i \, IIS_t + \sum_1^T \tau_i \, SIS_t + \sum_1^T \varphi_i \, DIIS_t + \sum_1^T \omega_i \, TIS_t + \varepsilon_t. \tag{A1}$$

Here,

IIS_t = impulse-indicator saturation, which takes a value of one at time t and a value of zero otherwise;

SIS_t = step-indicator saturation, which takes a value of one until time t and a value of zero otherwise;

$DIIS_t$ = differenced impulse-indicator saturation, which takes a value of one at time t, a value of -1 at time t+1 and a value of zero otherwise;

TIS_t = trend-indicator saturation, which takes a value of zero after time t+1, a value of -1 at time t, a value of -2 at time t-1, a value of -3 at time t-2 and so forth.

$\alpha_i, \vartheta_i, \tau_i, \varphi_i, \omega_i$ are regression coefficients to be estimated, and ε_t is a random error term with $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$.

$\alpha_i, \vartheta_i, \tau_i, \varphi_i, \omega_i$ are regression coefficients to be estimated, and ε_t is a random error term with $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$.

The modeling procedure using the autometrics algorithm consists of two steps (e.g., Castle, Hendry, and Martinez [2017]; Hendry [2020]). The first step involves fixing the constant term and all four lagged values of the dependent variable. In this step, the algorithm searches for and chooses the intervention dummies using a very tight significance level (0.01%). The identified specification is considered to be the general unrestricted model. The second step involves fixing the dummies chosen in the first step and unfixing the four lagged values of the dependent variable to search for the final specification. This specification is chosen based on the congruency criterion and multiple diagnostic tests. Given our baseline forecasting purposes, we use a relatively loose significance level (10%), as Castle, Doornik, and Hendry (2021) suggest. The multipath selection procedure is performed using the PcGive-15.10 econometric modeling program (Doornik and Hendry 2018). The final chosen specification is then used to produce a baseline forecast.

A.2.2. Structural Time Series Model

The structural time series model (STSM) models a variable, such as total CO2 emissions, using a stochastic trend. As Harvey (1989) notes, this stochastic trend captures long-term movements in a time series variable that can be extrapolated into the future. The simplest STSM consists of a stochastic trend and a random disturbance term. To capture autoregressive behavior and ensure consistency between approaches, we start with the same autoregressive equation with four lags as the one used in the autometrics approach. We model the natural logarithm of total CO2 emissions as follows:

$$co_{2_t} = \gamma_t + \alpha_1 co_{2_{t-1}} + \alpha_2 co_{2_{t-2}} + \alpha_3 co_{2_{t-3}} + \alpha_4 co_{2_{t-4}} + \varepsilon_t. \tag{A2}$$

Here, γ_t is the stochastic trend, which is also interpreted as a time-varying intercept, and ε_t is a random error term with $\varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$.

The stochastic trend consists of a level μ_t and a slope β_t , which are defined as follows:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \tag{A3}$$

$$\beta_t = \beta_{t-1} + \xi_t. \tag{A4}$$

Here, $\eta_t \sim NID\ (0, \sigma_\eta^2)$ and $\xi_t \sim NID\ (0, \sigma_\xi^2)$ are mutually uncorrelated random disturbance terms. If the variance of either η_t or ξ_t is zero, then that component of the trend is deterministic. If both hyperparameters are zero, then the stochastic trend collapses into a deterministic trend.

As in the autometrics approach, we can identify different types of dummy variables (i.e., irregular, level and slope interventions) to add to the model (Harvey and Koopman 1992). These interventions capture important breaks and structural changes on certain dates during the estimation period. They can be incorporated into the stochastic trend, which is defined as follows:

$\gamma_t = \mu_t$ irregular interventions (Irr) + level interventions (Lvl)+ slope interventions (Slp).

We start by estimating Eqs. (A2), (A3) and (A4) using the maximum likelihood method coupled with the Kalman filter using the software package STAMP 8.40 (Koopman et al. 2007). Appropriate irregular, level and slope interventions are identified and included in the model, and statistically insignificant lagged dependent variables are excluded. We also ensure that the estimated final specification passes an array of standard diagnostic tests.[1] Finally, the auxiliary residuals associated with the irregular, level and slope components cannot suffer from non-normality. This procedure produces a final, preferred specification that can be used to generate a baseline forecast.

A.2.3. Forecast Combination

Forecast combination is widely used to improve the quality and accuracy of forecasts made by different models. Bates and Granger (1969), Hansen (2008) and Clements and Hendry (1998) describe the theoretical statistical advantages of forecast combination. Because they perform well, forecast combinations are widely used in empirical and practical research. For example, Guidolin and Timmermann (2009) propose a flexible forecast combination approach and use it to forecast short-term interest rates in the United States (U.S.). Song et al. (2009) investigate the performance of forecast combination approaches over various time horizons in the context of tourism demand forecasting. Their statistical assessments of combined and single-model forecasts show that combined forecasts are much more accurate than average single-model forecasts. This result holds across all forecasting horizons and for all combination procedures.

Bjørnland et al. (2012) use forecast combination to improve the individual forecasts from different models of inflation in Norway. Baumeister and Kilian (2015) explore the advantages of forecast combinations among models of crude oil prices. The combined forecasts perform better, and they conclude that properly constructed forecast combinations should replace conventional judgmental forecasts of oil prices. To improve inflation forecasts for the U.S., Zhang (2019) employs real-time macroeconomic information and combination forecasts with both time-varying and equal weights.

A.3. Preferred Estimated Specifications

A.3.1. Autometrics

Table A1 provides full details of the preferred autometrics specification that we obtain using our methodology. The equation is well specified and passes all diagnostic tests. It includes two statistically significant lagged dependent variable terms: a one-year lag and a two-year lag. The coefficient of the one-year lag is positive and greater than one. The coefficient of the two-year lag is negative but smaller than the coefficient of the one-year lag in absolute terms. Thus, the coefficients have a positive combined effect of slightly less than one. Only one impulse indicator is retained in the model following the autometrics selection procedure. Thus, with no other interventions and a positive overall effect of the estimated coefficients, CO2 emissions are projected to grow in the baseline. This outcome is reasonable for a developing economy, such as Saudi Arabia.

Table A1. Preferred autometrics specification.

Time period	1984 to 2019		
Estimated coefficients		***Residual diagnostics***	
α_0	0.1421*	*AR(1-2)*	0.76
α_1	1.2878***	*ARCH (1-1)*	0.23
α_2	-0.3079**	*Normality*	2.75
α_3	-	*Hetero*	0.69
α_4	-	*Hetero-X*	0.54
		RESET	2.00
Interventions/indicator			
Impulse 1984	-0.1857***		
Goodness of fit			
R^2	0.995		
$\bar{R}^2$	0.994		
F	2107		

Source:Notes: *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively. R^2 is the coefficient of determination, and $\bar{R}^2$ is the adjusted coefficient of determination. F is the overall goodness-of-fit statistic and follows an $F_{(3, 23)}$ distribution. AR(1-2) is the second-order autocorrelation statistic, which follows an $F_{(2, 30)}$ distribution. ARCH (1-1) is the first-order autoregressive conditional heteroskedasticity statistic, which follows an $F_{(1, 34)}$ distribution. Normality is reflected by the Doornik and Hansen statistic, which follows an approximate $\chi^2_{(2)}$ distribution. Hetero and hetero-x are heteroscedastic statistics that follow $F_{(4, 30)}$ and $F_{(5, 29)}$ distributions, respectively. RESET is the Ramsey RESET statistic, which follows an $F_{(2, 30)}$ distribution.

A.3.2. STSM

Table A2 provides full details of the preferred STSM specification that we obtain using our methodology. Similar to the autometrics model, the preferred model is well specified, passing all diagnostic tests. The model includes one-year and three-year lags of the dependent variable. The coefficient of the one-year lag is positive. The coefficient of the three-year lag is negative and slightly larger than the one-year lag coefficient in absolute terms. The coefficients therefore have a slightly negative combined effect of about -0.07. Thus, the lagged coefficients suggest a slight decrease in overall emissions in the future. By contrast, the trend estimated through the STSM approach is strongly upward sloping. It offsets the overall small negative effect of the estimated coefficients, producing upward-sloping emission projections. The preferred specification also includes several interventions, as Table A2 shows.

The trends and their components are presented in Figure A1. The trend for the preferred STSM specification has a deterministic level and a stochastic slope. The stochastic slope is shown in Figure A1, Part A and is nonlinear with increasing and decreasing periods. Notably, the estimated slope declines sharply in 2015. By contrast, the level component shown in Figure A1, Part B is somewhat linear. The overall trend is a combination of the level component and the interventions and is shown in Figure A1, Part C. It has an upward trajectory with a sharp kink in the mid-2000s. This kink is due to the decrease in the slope component and the negative 2015 slope intervention, which slows the trend's overall growth rate.

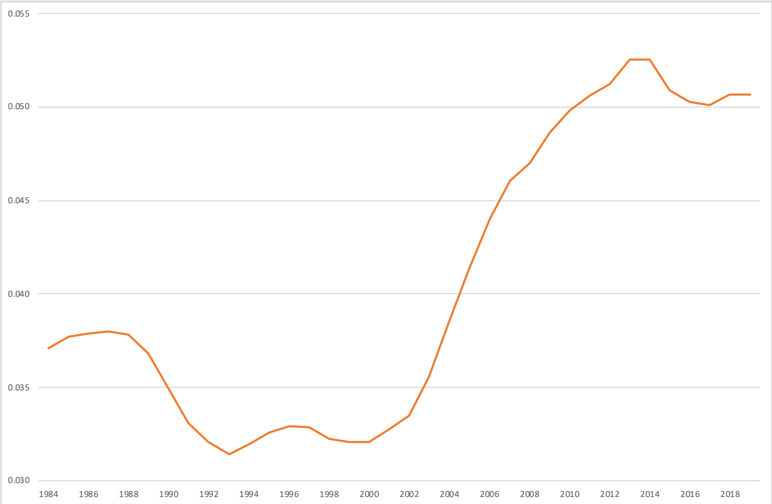
Table A2. Preferred STSM specification.

Time period	1984 to 2019		
Estimated coefficients		***Residual diagnostics***	
α_1	0.5803***	*Normality*	0.66
α_2	-	*H(8)*	4.46
α_3	-0.6591***	*r(1)*	-0.12
α_4	-	*r(2)*	-0.02
Interventions/indicator		*r(3)*	0.13
Level 1987	-0.0787***	*r(6)*	0.03
Irregular 1989	-0.0638***	*DW*	2.16
Level 1991	0.0882***	*Q(6,4)*	1.85
Irregular 1996	0.0711***	***Auxiliary residuals:***	
Slope 2001	0.0163*	*Normality - Irregular*	0.64
Irregular 2010	0.0300**	*Normality - Level*	0.84
Slope 2015	-0.0525***	*Normality - Slope*	1.03
Interventions/indicator	Fixed level	***Prediction failure***	11.08
	Stochastic slope		
Goodness of fit			
p.e.v.	0.00023634		
AIC	-7.6836		
BIC	-7.1557		
R^2	0.999		
R_d^2	0.881		

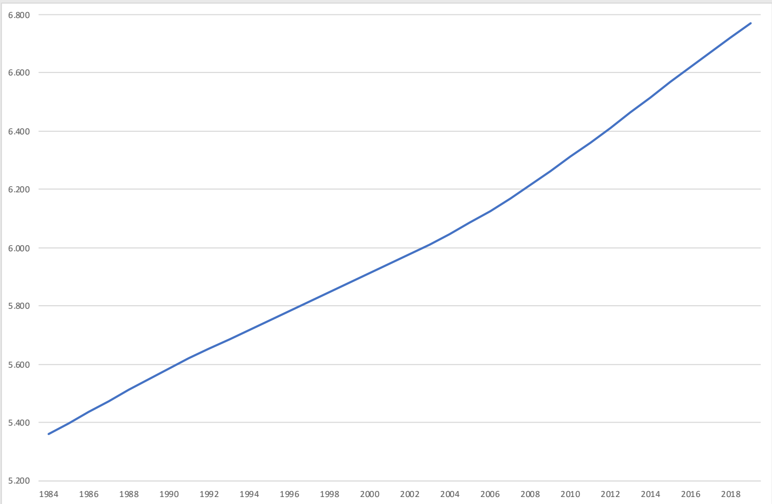
Source:Notes: *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively. R^2 is the coefficient of determination, and R_d^2 is the coefficient of determination based on differences. *p.e.v.* is the prediction error variance. AIC is the Akaike information criterion, and BIC is the Bayesian information criterion. Normality is determined based on the Bowman-Shenton statistic, which follows an approximate $\chi^2_{(2)}$ distribution. H(8) is a heteroscedasticity statistic that follows an $F_{(8, 8)}$ distribution. r(1), r(2), r(3) and r(6) are the serial correlation coefficients at the equivalent residual lags and are approximately normally distributed. DW is the Durbin-Watson statistic. Q(6,4) is the Box-Ljung statistic, which follows a $\chi^2_{(4)}$ distribution. The prediction failure is a predictive failure statistic that follows a $\chi^2_{(7)}$ distribution.

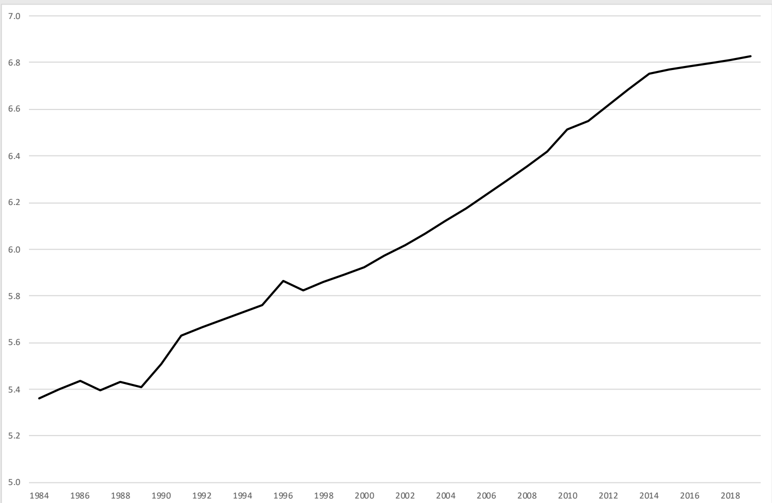
Figure A1. Estimated slope (β), level (μ) and trend (γ) of the preferred STSM specification.

A: Slope component of the estimated trend



B: Level component of the estimated trend





Endnotes

[1] These tests are detailed in the results section.

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Jeyhun is a fellow at KAPSARC. He received his B.A. and M.S. from Azerbaijan State University (now Baku State University) in Mathematics. Jeyhun holds a Ph.D. in Applied Mathematics and a D.S. in Econometrics. Before joining KAPSARC in September 2017, Jeyhun was an associate professor at the Department of Statistics and Econometrics at Azerbaijan State University, and the Department of Economics at Qafqaz University, where he taught econometrics, statistics, and mathematical economics. His other roles have included director of the Research Institute for Social Sciences and Humanities, and head of the Center for Socio-Economic Research. Jeyhun was a postdoctoral researcher at Indiana University Bloomington, United States (U.S.). He has also been a visiting researcher at several institutions, including the Center for Econometric Research, Sungyunkwan University in Seoul, South Korea; Vistula University, Warsaw, Poland; the University of North Texas, and the University of South Texas. Jeyhun's research is focused on applied time series econometrics, the economics of energy, the environment and sustainable development. He has authored over 40 scientific articles published in peer-reviewed journals and is an editorial board member of the International Journal of Advanced Multidisciplinary Research and Review, the Journal of Management, Economics and Industrial Organization, and the Journal of Socio-Economic Studies. He is also a member of the International Association for Energy Economics.

About the Project

This project Modeling Energy Demand, Greenhouse Gas Emissions, and the Impacts of Energy Price Reform seeks to provide an in-depth understanding of the relationships between energy demand, CO2 emissions, and energy price reform in Saudi Arabia. One of its key focus areas is understanding the potential evolution of domestic energy demand and greenhouse gas emissions in Saudi Arabia.

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