Forecasting Saudi Arabia's 2060 Carbon Dioxide Emission Pathways: A Multivariate Approach

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Overview

Saudi Arabia, a party to the Paris agreement, has committed under its new nationally determined contribution to become carbon net-zero by 2060. However, Saudi Arabia's baseline emission scenario has not been made public. This paper uses STSM[1] and Autometrics techniques to model two emission paths through a multivariate approach that factors in various emission impacting variables, such as GDP, aggregate energy price index, and value-added sectors. We forecast emission paths based on our estimated models and extend them to the future to provide two projections. These scenarios differ in their estimation and the underlying assumptions. Our preliminary projections assume no additional policies to curb emissions will be undertaken. Under these assumptions, CO2 emissions in Saudi Arabia would grow from 540 Mt in 2019 to 944 Mt, as a lower bound, and up to 1228 Mt by 2060, based on the chosen model.

Methods

To our knowledge, multivariate STSM and Autometrics has not been used for GHG baseline forecasting for Saudi Arabia. We take advantage of two methods to explain the data with unique abilities to capture trends and interventions throughout time. These interventions allow us to reflect the impact of shocks and policy change on GHG emissions, and their omission can lead to biased estimation. It is worth noting that while both STSM and Autometrics capture interventions, they differ in the approach.

The estimation procedure starts with a consistent general model to ensure model comparability between the methods with both approaches modelling the natural logarithm of Saudi CO_2 emissions (Mt) denoted by lower-case co_{2_t} with a vector of drivers $\boldsymbol{X}_t$ where t denotes the year. An autoregressive behaviour in the general equations is included, and a 'preferred' or 'final' equation is obtained by adding statistically significant interventions (also known as dummy variables) and dropping the insignificant right-hand side variables while monitoring an array of diagnostic tests. The preferred estimated equations are then used to produce the projections of Saudi CO_2 emissions to 2060 with the final projections being the average of the STSM and Autometrics projections, which is consistent with Enders (2015).

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

$$co_{2_t} = \alpha_0 + \alpha_1 co_{2_{t-1}} + \alpha_2 \boldsymbol{X}_t + \alpha_3 \boldsymbol{X}_{t-1} + \textstyle\sum_1^T \vartheta_i \, IIS_t + \sum_1^T \tau_i \, SIS_t + \sum_1^T \varphi_i \, DIIS_t + \sum_1^T \omega_i \, TIS_t + \varepsilon_t \qquad (1)$$

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, and TIS_t is a Trend-Indicator. $\alpha_i, \vartheta_i, \tau_i, \varphi_i, \omega_i$ are regression coefficients to be estimated; and ε_t *is* a random error term $\sim NID\ (0, \sigma_\varepsilon^2)$.

The STSM models GHG 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:

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

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

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \qquad (3a)$$
$$\beta_t = \beta_{t-1} + \xi_t \qquad (3b)$$

where $\eta_t \sim NID\ (0, \sigma_\eta^2)$ and $\xi_t \sim NID\ (0, \sigma_\xi^2)$ are mutually uncorrelated random disturbance terms. If the variances of either η_t or ξ_t are found to be zero, that component of the trend becomes deterministic. If both hyperparameters are found to be zero, the stochastic trend collapses into a deterministic trend. Like Autometrics, different types of dummy interventions can be identified and added to the model (Harvey and Koopman, 1992). These interventions capture

[1] STSM refers to Structural Time Series Model

important breaks and structural changes at certain dates during the estimation period. These interventions can be incorporated into the stochastic trend, which can be defined as follows:

$$\gamma_t \quad = \quad \mu_t + \text{irregular interventions } (Irr_t) + \text{level interventions } (Lvl_t) + \text{slope interventions } (Slp_t) \tag{4}$$

Results

So far, we have estimated the two sets of models highlighted below (both for the period 1985-2019). Further sets will be considered. In the first set, $\boldsymbol{X}_t$ consists of the natural logarithms of real GDP (gdp_t) and the real energy price (p_t). The preliminary estimated preferred models for this set for both Autometrics and the STSM, respectively are given by:

$$\widehat{co_2}_t = 5.3332^{***} + 0.1306^{**} gdp_t - 0.1366^{***} p_t - 0.0540^{**} SIS_{1986} + 0.0588^{***} TIS_{1992} - 0.0548^{***} TIS_{1993} + 0.0437^{***} TIS_{2015} \tag{5}$$

$$\widehat{co_2}_t = \hat{\gamma}_t + 0.1913^{**} gdp_t - 0.1324^{***} p_t \tag{6a}$$

with the estimated trend ($\hat{\gamma}_t$) given by $\hat{\gamma}_t = \hat{\mu}_t + 0.0500^{**} Irr_{1988}$ (6b)

For the second set, in the general model $\boldsymbol{X}_t$ consisted of the natural logarithms of Value Added for Agriculture ($agva_t$), Manufacturing ($manva_t$), and Services ($servva_t$), and the real energy price (p_t). After testing down, the preliminary estimated preferred models for this set for both Autometrics and the STSM, respectively are given by:

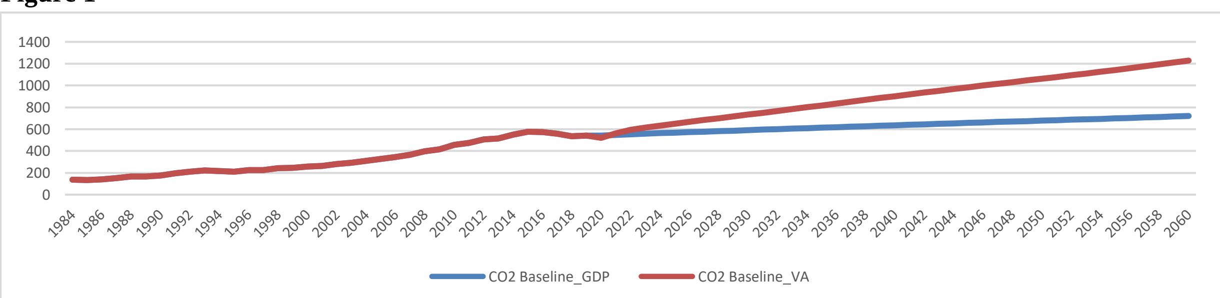
$$\widehat{co_2}_t = -2.2140^{***} + 0.4052^{***} co_{2_{t-1}} + 0.7342^{***} manva_t - 0.2504^{***} manva_{t-1} - 0.0483^{***} p_t + 0.0459^{**} IIS_{2002} - 0.0985^{***} SIS_{1990} + 0.0661^{***} SIS_{1993} + 0.0562^{***} TIS_{1987} - 0.0521^{***} TIS_{1996} + 0.0507^{***} TIS_{1997} \tag{7}$$

$$\widehat{co_2}_t = \hat{\gamma}_t + 0.3986^{***} manva_t + 0.4875^{***} agrva_t - 0.1054^{***} p_t \tag{8a}$$

with the estimated trend ($\hat{\gamma}_t$) given by $\hat{\gamma}_t = \hat{\mu}_t + 0.0500^{**} Lvl_{1991}$ (8b)

Where, the *, **, and *** represent coefficients significant at the 10%, 5%, and 1% levels, respectively and $\hat{\mu}_t$ represents the estimated level component of the trend. Each of the estimated equations in each set are used to produce projections for Saudi CO_2 emissions up to 2060 and an average taken within each set to produce the baseline scenarios (CO2 Baseline GDP and CO2 Baseline VA) shown Figure 1.

Figure 1



Conclusions

Our preliminary baseline projections suggest that if current trends, drivers, and policies in 2019 were extended into the future and no further policies to curb emissions were undertaken, for Saudi Arabia, CO2 emissions would grow from 540 Mt in 2019 to 944 Mt in 2060, and up to1228 Mt by 2060 based on the chosen model. It is important to note that there are significant uncertainties around these estimates. The finalized projected baseline scenarios will be valuable tools for policymakers, highlighting the efforts needed to achieve Saudi Arabia's climate goals. It will illustrate how those efforts could push Saudi's baseline GHG emissions onto a more sustainable pathway.

References

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