Baseline greenhouse gas forecasts for Saudi Arabia using the Structural Time Series Model and Autometrics

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Overview

As a party to the Paris Agreement, Saudi Arabia submitted a baseline target to reduce its emissions as part of its nationally determined contribution (NDC). Baseline targets rest on the development of a baseline emissions scenario. Saudi Arabia's baseline scenario has not yet been made publicly available. In this paper we use two different econometric methods within a univariate framework to develop baseline greenhouse gas (GHG) emission forecasts, extending current drivers, trends, and policies into the future without the need to make assumptions about factors such as economic growth in the coming decades. The different methods are used since they provide a robustness check, as each method has its strengths and weaknesses. We therefore combine both methods by averaging to generate our baseline GHG emissions projections for Saudi Arabia.

Methods

As far as we are aware, neither the STSM nor Autometrics have been used for GHG baseline forecasting. We use these two methods given their ability to explain the data with a combination of trends and interventions. These interventions can capture the effects of shocks and policy changes on GHG emissions, and their omission could lead to biased estimation results. Although both the STSM and Autometrics capture interventions, they differ in the way in which they do so.

To ensure comparability between the methods, we start the estimation procedure with a consistent general univariate model. In both approaches, we model the natural logarithm of the different GHG emissions (carbon dioxide – CO_2, methane – CH_4, and nitrous oxide – N_2O) denoted generally by lower-case ghg_t, where t denotes the year. Four lags of the dependent variable are included to capture autoregressive behaviour in the general equations, 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 baseline projections of the different GHG emissions for Saudi Arabia to 2060 with the final projections for each GHG being the average of the STSM and Autometrics projections, 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:

$$ghg_t = \alpha_0 + \alpha_1 ghg_{t-1} + \alpha_2 ghg_{t-2} + \alpha_3 ghg_{t-3} + \alpha_4 ghg_{t-4} + \sum_1^T \vartheta_i \, IIS_t + \sum_1^T \tau_i \, SIS_t + \sum_1^T \varphi_i \, DIIS_t + \sum_1^T \omega_i \, TIS_t + \varepsilon_t \quad (1)$$

where 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:

$$ghg_t = \gamma_t + \alpha_1 ghg_{t-1} + \alpha_2 ghg_{t-2} + \alpha_3 ghg_{t-3} + \alpha_4 ghg_{t-4} + \varepsilon_t \quad (2a)$$

where α_i are regression coefficients to be estimated, γ_t is a stochastic trend (or time varying intercept) and ε_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:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad (2b)$$
$$\beta_t = \beta_{t-1} + \xi_t \quad (2c)$$

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 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:

$$\gamma_t = \mu_t + \text{irregular interventions } (Irr_t) + \text{level interventions } (Lvl_t) + \text{slope interventions } (Slp_t) \quad (2d)$$

Results

The estimated preferred models for CO_2, CH_4, and N_2O emissions for Saudi Arabia for both econometric techniques are given below:

***CO_2* (1984-2019) Autometics:** $\widehat{co_2}_t = 0.1421^{*} + 1.2878^{***}co_{2_{t-1}} - 0.3079^{**}co_{2_{t-2}} - 0.1857^{***}IIS_{1984}$ (3)

***CO_2* (1984-2019) STSM:** $\widehat{co_2}_t = \hat{\gamma}_t + 0.5803^{***}co_{2_{t-1}} - 0.6591^{***}co_{2_{t-3}}$ (4a)

with the estimated trend ($\hat{\gamma}_t$) given by $\hat{\gamma}_t = \hat{\mu}_t - 0.0787^{***}Lvl_{1987} - 0.0638^{***}Irr_{1989} + 0.0882^{***}Lvl_{1991} + 0.0711^{***}Irr_{1996} + 0.0163^{*}Slp_{2001} + 0.0300^{**}Irr_{2010} - 0.0525^{***}Slp_{2015}$ (4b)

***CH_4* (1988-2019) Autometics:** $\widehat{ch_4}_t = 1.3636^{***} + 0.6965^{***}ch_{4_{t-1}} + 0.2069^{*}ch_{4_{t-2}} - 0.1871^{**}ch_{4_{t-3}} - 0.0566^{***}DIIS_{1999} - 0.0493^{***}DIIS_{2002} + 0.1135^{***}IIS_{1991} + 0.0072^{***}TIS_{2017}$ (5)

***CO_2* (1988-2019) STSM:** $\widehat{ch_4}_t = \hat{\gamma}_t + 0.5333^{***}ch_{4_{t-1}} - 0.2007^{*}ch_{4_{t-2}} + 0.3386^{***}\Delta ch_{4_{t-3}}$ (6a)

with the estimated trend ($\hat{\gamma}_t$) given by $\hat{\gamma}_t = 2.6706^{***} + 0.0160^{***}t - 0.1983^{***}Irr_{1989} - 0.0767^{***}Irr_{1999} - 0.0578^{***}Irr_{2009}$ (6b)

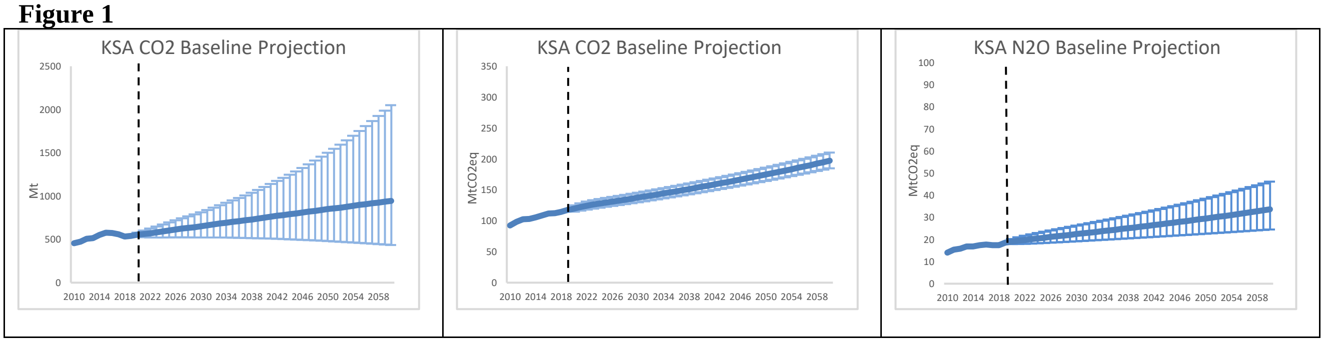
***CH_4* (1984-2019) Autometics:** $\widehat{n_2o}_t = 0.4117^{***} + 0.8635^{***}n_2o_{t-1} - 0.0880^{***}DIIS_{1995} - 0.0719^{***}DIIS_{1996} + 0.0664^{***}SIS_{2007} - 0.1072^{***}SIS_{2009}$ (5)

***N_2O* (1984-2019) STSM:** $\widehat{n_2o}_t = \hat{\gamma}_t + 0.4089^{***}n_2o_{t-1}$ (6a)

with the estimated trend ($\hat{\gamma}_t$) given by $\hat{\gamma}_t = \hat{\mu}_t - 0.0736^{***}Irr_{1995} - 0.1186^{***}Lvl_{2008}$ (6b)

Where, the *, **, and *** represent coefficients' significance at the 10%, 5%, and 1% levels, respectively and $\hat{\mu}_t$ represents the estimated level components of the trends. Each of these estimated equations are used to project emissions for Saudi Arabia up to 2060 and a simple average taken for each GHG to represent the baseline scenario given in Figure 1 with their 95% confidence intervals.

Figure 1



Conclusions

Our baseline projections suggests 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, CO_2 emissions would grow from 540.4 Mt in 2019 to 651.2 Mt by 2030 and 944.4 Mt by 2060, CH_4 emissions would grow from 117.5 $MtCO_2eq$ in 2019 to 137.5 $MtCO_2eq$ by 2030 and to 197.2 $MtCO_2eq$ in 2060, and N_2O emissions would grow from 18.6 $MtCO_2eq$ in 2019 to 22.4 $MtCO_2eq$ by 2030 and to 33.7 $MtCO_2eq$ in 2060.

Of course, there are large uncertainties around these estimates; nevertheless, the finalized projected baseline scenarios will be valuable tools for policymakers, providing an indication of the efforts needed to achieve Saudi Arabia's climate goals, in the near and long terms, and illustrating how much those efforts could push Saudi's baseline GHG emissions onto a more sustainable pathway.

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