# The Devil is in the Detail: Simple Projections of Atmospheric Carbon

Econometrics Games Case A Report

Team 20

## Abstract

Models of atmospheric carbon concentrations are crucial to evaluating how much emission reduction will be required to contain global temperature increases to acceptable levels. The growth of atmospheric carbon depends on the balance between human sources of emissions and natural biosphere sinks, with feedback mechanisms between atmospheric carbon concentration and sinks playing an important role. We develop a system of simple statistical models utilising the Global Carbon Budget framework and estimate it on data over 1959–2017 from the Global Carbon Project (Le Quéré et al., 2018). We use the model to project emissions, sinks and atmospheric carbon concentration to 2100 and compare these with scenarios from the Representative Concentration Pathways initiative. Our baseline model predicts a levelling out of atmospheric carbon growth at around 6 GtC/yr and a declining atmospheric fraction. However, we show that the feedback mechanism plays a critical role in the model dynamics and emphasise the uncertainty of our results in this respect.

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# 1 Introduction

Carbon dioxide is a key component of atmospheric greenhouse gases responsible for warming the planet. Starting from the Industrial Revolution in the middle of the 18th century, human economic activities have been a key driver in increasing atmospheric carbon concentration, through fossil fuels use, industrial production and changes in land-use. The extra carbon in the air traps more refracted energy from the Earth's surface, driving mean temperature upwards and producing potentially profound climatic change.

This paper develops a statistical model, using the Global Carbon Budget framework from the Global Carbon Project (Le Quéré et al., 2018), to link anthropogenic carbon emissions to increasing atmospheric carbon concentration. Specifically, global emission from either fossil fuel uses or land-use changes can be absorbed by the ocean, land or retained in the atmosphere. Growth in atmospheric carbon concentration is then forecast for every year until the end of this century.

The model utilises simple univariate time-series techniques to extrapolate fossil fuel and land-use change emissions. Equations for land and ocean sinks are augmented to the system, and allowed to react to the level of atmospheric carbon concentration. The key identifying assumption used to overcome endogeneity between atmospheric carbon growth and biosphere sink is a simple timing restriction – sinks only react to lagged concentration levels. The equations for emissions and sinks are coupled with identities, including the global carbon budget, and projections are estimated using stochastic simulation.

The model projects an upwards trend for atmospheric concentration, with concentration level reaching around 700 GtC by 2100. This result comes from atmospheric carbon concentration being predicted to grow positively every year until the end of the century, however, the growth flattens out over time. By around 2070, atmospheric concentration is expected to grow at a rate of about 6 GtC / yr - a rate that does not change much for the next 30 years. The concave growth curve comes from a positive relationship predicted between atmospheric concentration level and sink amount (both oceanic and land). Thus, the model's assumption of sink amount being linked to past concentration level is a crucial one that underlines our predictive results.

We can also use the model to reverse engineer emission trajectories: that is, given an atmospheric concentration pathways, it is possible to recover the implied emission timepath. This exercise was done using the four scenarios from the Representative Concentration Pathways initiative (Meinshausen et al., 2011). They describe possible future carbon concentration projections between 2019 and 2100, ranging from a $1.5^oC$ increase scenario (active global climate policies and controlled growth), to a catastrophic $4.5^oC$ increase one (strong population growth and weak climate policies).

Our result shows that to reach the most moderate future, with $1.5^oC$ increase only, emission would need to be brought down substantially. Specifically, emission needs to immediately drop and reach the 1960-1960 levels by 2100. This is a tall order, taking into account projected future economic and population growth - especially among developing nations. Projection using current baseline mean emission indicates the world is likely on the intermediate scenario. The catastrophic scenario occurs when emission is left to not simply increase, but grow at a higher rate than currently found - in this world, anthropogenic emission reaches nearly 50 GtC / yr by 2100, an increase of about 5 times compared to 2018 level.

The report is organized as follow: Section 2 describes the background on the relationship between man-made emission and atmospheric carbon concentration, and the potential climate impacts. Section 3 reviews the literature surrounding the factors in the Carbon Budget Equation. Section 4 describes the dataset given by Le Quéré et al. (2018) as well as constructed variables needed for the model. Section 5 lays out the baseline model and the predictive algorithm. Section 6 evaluates the model against several alternatives, presents the projected atmospheric concentration level to 2100, explore the aforementioned feedback mechanism further, and presents the emission pathways under different RCP scenarios. Section 7 discusses our results, and compare them to the broader literature. Section 8 concludes.

## 2 Background

Carbon on Earth can be found everywhere: in rock, in the ocean, in the soil, the air, and in all living creatures. Human and natural activities move carbon gases around these reservoirs in the carbon cycle, which has regulate the earth's temperature for a few hundred thousand years Riebeek & NASA (2011). Living creatures engender a "fast" cycle through photosynthesis, decaying, breathing, eating,... while chemical reactions and tectonic activities create a "slow" cycle. Intense anthropogenic activities in burning fossil fuels and changing land use have, however, shift carbon from the "slow" to the "fast" cycle at an alarming rate: about 8.4 billion tons of carbon was released through fossil fuel burning in 2009.

Increasing carbon concentration in the Earth's atmosphere will lead to a higher average temperature on the planet. Carbon dioxide in the air traps long-wave radiation emitted from the Earth's surface, absorbing strongly around $15\mu m$ near the peak of the long-wave, ensuring that the global surface stays high (Mitchell, 1989). Consequently, the gas contributes to about 20% of Earth's greenhouse effect (Riebeek & NASA, 2011). Human activities are estimated to have caused about $1.0^oC$ of global warming above pre-industrial levels, and will likely reach $1.5^oC$ between 2030 and 2050 if it continues at the current rate (Allen et al., 2018).

The potential impact of a higher mean temperature is many-fold. Polar ice caps melting will lead to a higher sea level, threatening human life in coastal and low-lying areas. Higher carbon concentration in the ocean increases acidity level, harming marine life. The probability of drought, extreme temperature and violent swing in precipitation across many regions will also increase (Allen et al., 2018).

Due to the implication of higher atmospheric carbon concentration on the Earth's climate, deeper understanding of the human-induced carbon cycle is vital. The Global Carbon Project, in particular, collects and publish data to create the Global Carbon Budget Equation:

Atmospheric carbon growth = emission (fossil fuel + land use) - carbon sink (land + ocean) + measurement/simulated error

The equation notes that if human carbon emission exceeds terrestrial and oceanic sink, the atmospheric concentration level will rise. Historical data indicates that fossil fuel emission rises to be the major component of anthropogenic carbon emission since 1950. Between 1959 and 2017, 82% of total emissions were from fossil fuel emission and 18% from land-use changes. (45%) of these carbon were sunk into the ocean, (30%) on land, and (45%) into the atmosphere (Le Quéré et al., 2018). The trend for anthropogenic emission has been upwards, driven by fossil emission: global level has increased every decade from an average of $3.1 \pm 0.2$ GtC yr$^{-1}$ in the 1960s to an average of $9.4 \pm 0.5$ GtC yr$^{-1}$ during 2008 - 2017, while emission from land use, land-use change and forestry has been relatively constant.

Given complex, intertwining factors affecting future human emission - the rise of developing economies, availability of alternative energy sources and the erratic climate political process - there are many pathways for future atmospheric carbon concentration. Meinshausen et al. (2011) present multiple times series for different atmospheric concentration possibilities in the Representative Concentration Pathways. These range from the RCP 2.6, representing a scenario where greenhouse gases are substantially controlled, with a global mean surface temperature increase of $1.5^oC$, to RCP 8.5, which see an increase of $4.5^oC$ due to strong population growth and slow technological change. The different scenarios force policymakers worldwide to consider what would happen under the present emission trajectory, or alternatively, what future emissions must be brought down to in order to achieve the desired concentration level.

# 3 Literature Review

Le Quéré et al. (2018) estimated the anthropogenic carbon dioxide ($CO_2$) emissions and their redistribution among the atmosphere, ocean, and terrestrial biosphere which are the five major components in the global budget equation. Substantial imbalances between the estimated emission level and the absorption level have been found. The mean of imbalances is 0.5 GtC / year for the period 2008-2017, which indicates either an overestimation of emission and/or underestimation of sinks. Such discrepancies may come from imperfect measurement and the fact that the models do not fully reflect the carbon cycle. This study provides the main dataset used in our study, the Global Carbon Budget Equation.

Raupach et al. (2014) argued that the combined land-ocean $CO_2$ sink rate provides a more direct assessment of the countervailing factors than focusing on the airborne fraction. They show that this rate declines over 1959–2012 by a factor of one third. They estimate that approximately 40 per cent of this reduction is attributable to intrinsic feedback responses of sink processes to changes in climate. They also argue that the balance of intrinsic and extrinsic drivers of the combined sink rate is crucial to predictions of atmospheric carbon.

Ballantyne et al. (2015) develop an approach to incorporate correlated errors into the structure of emissions estimates to better gauge uncertainty in the global carbon cycle. They find that uncertainty in atmospheric carbon estimates has declined, whereas uncertainty in fossil fuel emissions estimates has increased. On balance, this has resulted in a net decline in the uncertainty of net global carbon uptake around 20 per cent. The novel error structure generates estimates of land and ocean sink rates that have increased since 1959, in contrast to Raupach et al. (2014).

FRS Read (2001) focuses on the role of carbon sink in mitigating global climate change, noting that the 1997 Kyoto Protocol signatories can meet part of their obligation for reducing greenhouse gas emissions from increasing land carbon sinks. This was expected to come from changes in agricultural and forestry practices as well as slowdown in deforestation, though these actions require considerable political wills and cannot lead to ever-increasing rise in sink capacity. Furthermore, certain climate models project that future warming could diminish sink level in the future, and even convert the land into a source of $CO_2$ release. Our data indicates that carbon sink level has increased over the period 1959 to 2017, but has not been enough to absorb all the human-made emission and prevents a rise in atmospheric concentration.

# 4 Data

The main dataset obtained from Le Quéré et al. (2018) contains the times series needed for constructing the Global Carbon Budget Equation. These include the series for androgenic emissions, broken down into fossil fuels and land-use change, the atmospheric $CO_2$ growth rate, the amount of ocean sink, land sink and the budget imbalance. The report uses these time series for the period of 1959 to 2017, which are in Gigatones of carbon. For evaluating emission trajectories compatible with different concentration scenarios for 2019 - 2100 described by the RCPs, the report uses four scenarios from the RCP Database (Clarke et al., 2007; Fujino et al., 2006; Hijioka et al., 2008; Riahi et al., 2007; Smith & Wigley, 2006; van Vuuren et al., 2007; Wise et al., 2009). These hypothetical concentration series are originally in parts per million and shall be described in Section 6.4. Each of these series will now be described in details.

- Anthropogenic emissions:
  - Fossil fuel $CO_2$ emission is indirectly calculated from country-level energy statistics and cement production data. Statistics on coal, oil and gas for 1959 to 2014 comes from the CDIAC country-level dataset (Boden et al., n.d.), while that of 2014 to 2017 are from BP Statistical Review of World Energy (BP, 2018). Cement production data comes from Andrew (2018). Due to the indirect nature of the data, underlying biases in energy statistics and different accounting method used by each country, there is an uncertainty of ±5% for a ±1 sigma confidence level.
  - Land-use change emission is net emission from deforestation, afforestation, logging and forest degradation, shifting cultivation, and regrowth of forest (some of these activities may capture carbon instead of emitting). Data is simulated from two different bookeeping models (Hansis et al., 2015; Houghton & Nassikas, 2017), which keep track of carbon stored in vegetation and soils before and after a land-use change, as well as 16 Dynamic Global Vegetation Models (DGVMs) (Le Quéré et al., 2018). Since the models do not always agree, and there are difficulties in capturing the forces in the DGVMs, there is an uncertainty level of ±0.7 GtC / yr for this series
- Atmospheric concentration growth rate was directly measured by the US National Oceanic and Atmospheric Administration Earth System Research Laboratory from multiple measuring stations with well-mixed background air (Dlugokencky & Tans, 2018). There are several factors contributing to uncertainty surrounding the measurement: long-term reproducibility of reference gas standards, small unexplained systematic analytical errors lasting from several months to 2 years, the network composition of marine boundary layer site where stations are placed, and the approximation of true concentration using average $CO_2$ concentration from a surface network. They contribute to a variable uncertainty around 0.2 GtC/yr from 1980.
- Ocean $CO_2$ sink data was simulated from a group of biogeochemistry models (GOBMs), with calibration to fit the observational constraints on carbon sink level from the IPCC over the 1990s (mean 1990 sink of 2.2±0.4 GtC $yr^{-1}$) (Le Quéré et al., 2018). They do not include the effects of anthropogenic changes in nutrient supply, or the pertubation associated with changes in riverine organic carbon. The simulated data reflects our possibily limited understanding of the biogeochemical processes surrounding oceanic absoprtion of atmospheric carbon gasses, so the series has an uncertainty level of ±0.5 GtC/yr.

- Land or terrestrial CO2 sink data was simulated from the multi-model mean of different DGVMs simulation. This sinkage is thought to come from the effects of fertilisation through rising atmospheric $CO_2$ and $N$ deposition on plant growth, as well as climate change effect on growth season. Land sink data does not include land sinks directly from land use and land-use change, nor loss in sink capacity from land-use conversion. The uncertainty associated with land sink data is ±0.9 GtC / yr on average (Le Quéré et al., 2018).

- Budget imbalance is defined as the sum of emissions (fossil fuel and land-use change) minus absorption (atmosphere, ocean and land). In principle the Global Carbon Budget Equation should holds exact, and the imbalance should be 0, but due to the sources of measurement and/or estimation uncertainty mentioned, this is not necessarily the case (Le Quéré et al., 2018).

The six series just described are formally related through the Global Carbon Budget Equation as:

$$G_t^{ATM} = E_t^{FF} + E_t^{LUC} - S_t^{LND} - S_t^{OCN} + e_t$$

where $G_t^{ATM}$ is the amount of atmospheric carbon growth, $E_t^{FF}$ is fossil fuel emission, $E_t^{LUC}$ is land-use change emission, $S_t^{LND}$ is land sink amount, $S_t^{OCN}$ is ocean sink amount, and $e_t$ being the imbalance amount - all in yearly Gigatones of carbon level for the period 1959-2017. As mentioned, the equation describe how man-made carbon emissions are distributed among the reservoirs. Natural fluxes of $CO_2$ are excluded from all variables, as the equation only attempts to capture the anthropogenic contributions.

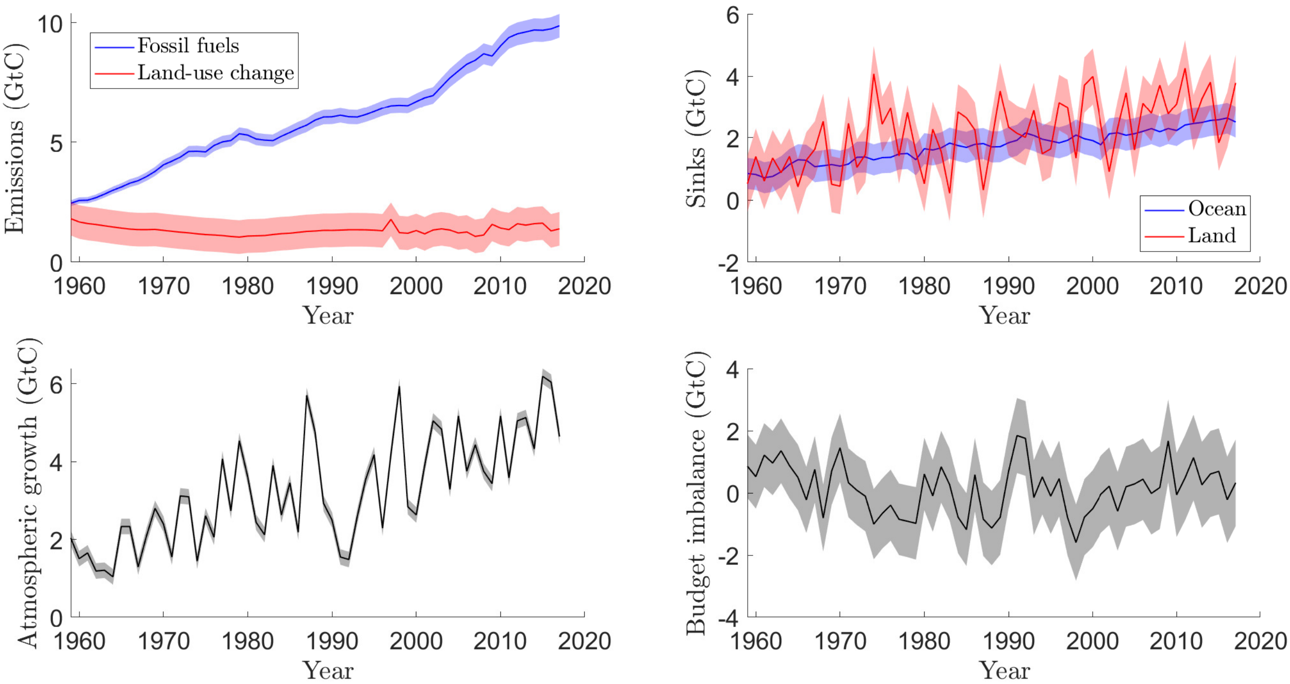



Figure 1: Components of Carbon Budget Equation (provided by data)

Figure 1 shows the components (solid lines) of the global carbon budget from year 1959 to 2017 and their individual uncertainties (shadow band) as described. The upper left sub-graph depicts emissions by sources. Land-use changes slightly decrease in the post-war years, but then stabilize around an average of 1.329 GtC / yr for most of the period of interest. In contrast, fossil fuel and industrial emissions has been steadily climbing up since WWII, from 2.453 GtC / yr in 1959 to 9.867 GtC / yr in 2017 - an increase of 302.24%. The upper right sub-graph shows the sink levels for land and ocean, with both having an upwards trend over time. Land sink is more volatile than volatile than ocean sink, and may have a cyclical component. The bottom two subplots are for atmospheric $CO_2$ growth (left) and budget imbalance (right). The rising trend for growth amount points to an alarming fact: atmospheric concentration has been growing at an increasing rate, implying that the "fast cycle" of anthropogenic emission has outstrip the "slow cycle" absorption of land and ocean sinks. Lastly, the budget imbalance fluctuated around its mean, 0.136 GtC / yr: the positive average indicates either an underestimation of sinks or overestimation of emissions or possibly both, as per Le Quéré et al. (2018).

Figure 2 shows the carbon budget equilibrium discarding the budget imbalance. The positive shades are the emissions, while are offset by the negative sinks. The resulting growth in atmospheric concentration is shown by the black solid line. This figure clearly reinforces our conclusion that although both emissions and sinks increased, the latter has not been enough to offset emissions, with the result being carbon gasses concentration in the atmosphere has risen.

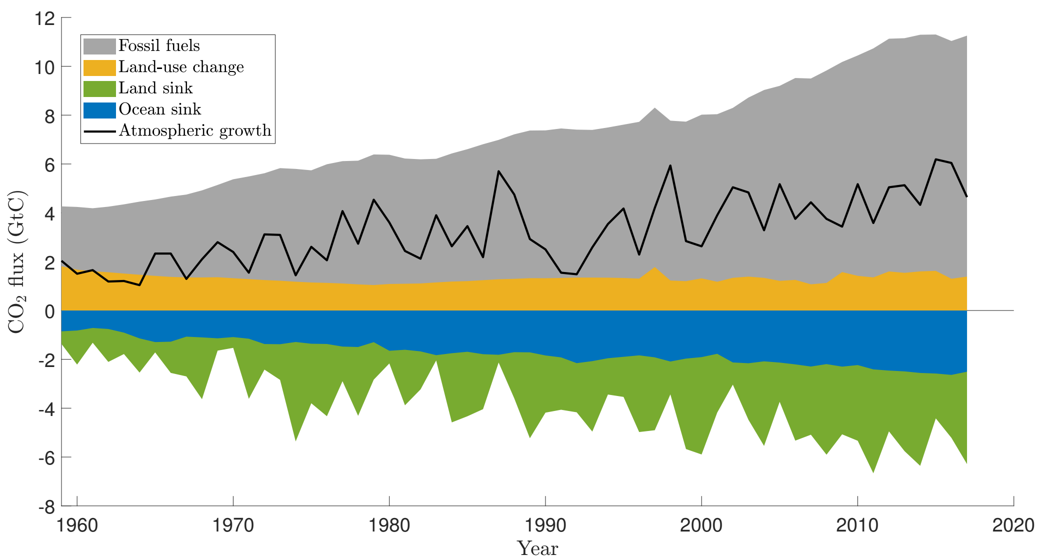



Figure 2: Components of Carbon Budget Equation (proportions)

Table 1 presents the Dickey-Fuller unit-root test which suggests that all data series do not have unit root except for emissions from fossil fuels. Meanwhile, emissions from fossil fuels is stationary after the the first difference.

### 4.1 New Variables Definition

We can think of the total amount of carbon dioxide in the atmosphere at any time as

$$C_t = C_0 + \int_0^T G_t^{ATM} dt$$

Table 1: Dickey-Fuller test of the Flow Variables

| Dickey-Fuller test | | Null Hypothesis: unit root | |
|---|---|---|---|
| Variable | | t-statistic | p-value |
| Emissions from fossil fuels | E_FF | -1.534 | 0.806 |
| First difference | $D\_E\_FF = E\_FF - E\_FF_{-1}$ | -5.289 | 0.000 |
| Emissions from land-use change | E_LUC | -3.961 | 0.016 |
| Ocean sink | S_OCN | -4.162 | 0.009 |
| Land sink | S_LND | -4.221 | 0.008 |
| Atmospheric $CO_2$ growth | G_ATM | -6.854 | 0.000 |

To generate the times series for total concentration, we need to calculate the initial level (year 1959), then use the growth series $G_t^{ATM}$ to trace out the timepath (Bennedsen et al., 2018). In particular, we utilize the following equation to calculate the concentrations in year 1959

$$C_{1959} = 2.127 \cdot ([CO_2]_{1959} - [CO_2]_{1750}),$$

where $[CO_2]_{1750} = 279$ ppmv is the preindustrial level serves as the benchmark for anthropogenic activity, $[CO_2]_{1959} = 315.39$ ppmv indicates the concentration level of the starting year in the data, and 2.127 is the conversion factor from ppmv to GtC. With the baseline level $C_{1959}$ measured in GtC, we can calculate the level of concentration for each year by

$$C_{year} = C_{1959} + \sum_{t=1959}^{year} G\_ATM_t.$$

The generated series is shown in figure 3, which is monotonically increasing and convex as expected from rising atmospheric carbon growth. It grows from 77.402 GtC /yr from 1959 to 267.629 GtC / yr in 2017.

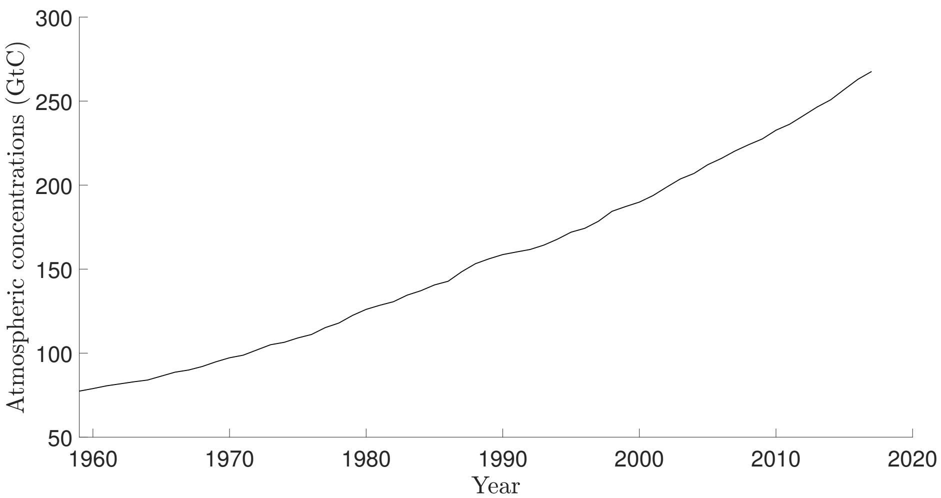



Figure 3: Atmospheric concentrations of $CO_2$ (GtC)

Furthermore, based on the fluxes of carbon dioxide, we define the airborne and sink fractions as per Raupach et al. (2014). The airborne fraction is the proportion of anthropogenic emissions leading to an increase in the atmospheric concentration of carbon dioxide,

$$AF_t = \frac{G_t^{ATM}}{E_t^{FF} + E_t^{LUC}}$$

whereas the sink fraction is the proportion being absorbed by the land and ocean,

$$SF_t = \frac{S_t^{LND} + S_t^{OCN}}{E_t^{FF} + E_t^{LUC}}$$

Note that the sink fraction also equals to

$$SF_t = 1 - AF_t$$

if the carbon budget equation holds exact. In our application, we use the first definition of the sink fraction.

# 5 Empirical Strategy and Model Specification

## 5.1 Baseline Model

In this section, we present a simple baseline model for the forecasting of the growth in atmospheric carbon dioxide. We begin by considering the the flow budget constraint given by

$$G_t = E_t^{FF} + E_t^{LUC} - S_t^L - S_t^O$$

where $E^{FF}$ and $E^{LUC}$ refer to emissions from fossil fuels and changes in land use respectively, whereas $S^L$ and $S^O$ refer to the absorption of carbon dioxide into the land and ocean respectively (known as land and ocean *sinks*). In this specification, $G_t$ refers to the atmospheric growth in carbon dioxide. Therefore, if we define $C_t$ as the atmospheric concentration of carbon dioxide, then

$$\begin{aligned} C_t &= C_{t-1} + G_t \\ &= C_0 + \sum_{j=1}^{t} G_j \end{aligned}$$

In this simple model, we suppose that the *sink* at any time is related to the atmospheric carbon concentration in the previous period. For the ocean sink, including a single lagged term improved the fit.

$$S_t^L = \beta_0^L + \beta_1^L C_{t-1} + e_t^L$$

and

$$S_t^O = \beta_0^O + \beta_1^O C_{t-1} + \beta_2^O S_{t-1}^O + e_t^O$$

where $\beta_1^L$ and $\beta_1^O$ are the sink *rates* (or efficiency) for land and ocean sinks, respectively. Modelling sinks as a function of atmospheric concentration is inspired by the data evidence and the previous studies. First, the above two regressions reveal significant correlation between sink and concentration and give a decent goodness of fit. Meanwhile, the sink rate is the main objective of previous studies (Bennedsen et al., 2018), and its sign is of academic dissensus.

In order to forecast the growth in carbon concentration, we require forecasts of the emissions, which will imply forecasts of the sinks in future periods through the total concentration of carbon. The key identification assumption of this model is that the sink rates are determined by past atmospheric carbon concentrations. We justify this assumption by noting that the concentration has a smooth trend in the levels rather than flow.

Based on the results from the unit root tests, we show that $E_t^{FF}$ is non-stationary, whereas $E_t^{LUC}$ is trend-stationary. Therefore, to forecast $E_t^{FF}$, we specify the following AR model in differences,

$$\Delta E_t^{FF} = \gamma_0 + \gamma_1 \Delta E_{t-1}^{FF} + \varepsilon_t^1$$

and forecast $E_t$ by accumulating the predicted first differences

$$E_t^{FF} = E_{t-1}^{FF} + \Delta E_t^{FF}$$

For $E_t^{LUC}$, we specified an AR(2) model, as suggested by the AIC, thus,

$$E_t^{LUC} = \delta_0 + \delta_1 E_{t-1}^{LUC} + \delta_2 E_{t-2}^{LUC} + \varepsilon_t^2$$

Therefore, to summarise, the forecast model is given by:

**(1)** Forecast the emissions:

(a) $\hat{E}_{t+1}^{LUC} = \delta_0 + \delta_1 E_t^{LUC} + \delta_2 E_{t-1}^{LUC}$

(b) $\Delta \hat{E}_{t+1}^{FF} = \gamma_0 + \gamma_1 \Delta E_t^{FF}$

(c) $\hat{E}_{t+1}^{FF} = E_t^{FF} + \Delta \hat{E}_{t+1}^{FF}$

**(2)** Forecast sinks:

(a) $\hat{S}_t^L = \beta_0^L + \beta_1^L C_{t-1}$

(b) $\hat{S}_t^O = \beta_0^O + \beta_1^O C_{t-1} + \beta_2^O S_{t-1}^O$

**(3)** Forecast growth using the flow budget constraint:

(a) $\hat{G}_{t+1} = \hat{E}_{t+1}^{FF} + \hat{E}_{t+1}^{LUC} - \hat{S}_{t+1}^L - \hat{S}_{t+1}^O$

**(4)** Calculate carbon dioxide stock for next period forecasts:

(a) $C_{t+1} = C_t + \hat{G}_{t+1}$

We note that the specification here assumes independence of shocks. As discussed in Ballantyne (2015), if this assumption were to not hold, the results may potentially be different. The parameter estimates for this model are given below

The model is estimated stochastically, with 1,000 pertubations which are used to generate the standard errors.

| | Point Est. | Std. Err. | $t$-stat | $p$-value |
|---|---|---|---|---|
| $\delta_0$ | 0.413 | 0.136 | 3.027 | 0.004 |
| $\delta_1$ | 0.460 | 0.132 | 3.471 | 0.001 |
| $\delta_2$ | 0.221 | 0.124 | 1.788 | 0.080 |
| $\gamma_0$ | 0.087 | 0.023 | 3.844 | 0.000 |
| $\gamma_1$ | 0.325 | 0.127 | 2.547 | 0.013 |
| $\beta_0^L$ | 0.486 | 0.350 | 1.386 | 0.171 |
| $\beta_1^L$ | 0.011 | 0.002 | 5.132 | 0.000 |
| $\beta_0^O$ | 0.164 | 0.058 | 2.827 | 0.007 |
| $\beta_1^O$ | 0.662 | 0.102 | 6.489 | 0.000 |
| $\beta_2^O$ | 0.003 | 0.001 | 3.107 | 0.003 |

Table 2: Parameter Estimates

# 6 Results

## 6.1 Model Evaluation

In order to evaluate our models, we consider the model fit and out of sample forecast performance. Firstly, we consider the model fit by calculating the root mean square error (RMSE) for within-sample prediction. We define the RMSE as

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t - \hat{Y}_t)^2}$$

where $Y_t$ is the data series and $\hat{Y}_t$ is the fitted series. We consider the forecast performance on the five main series, the fossil fuel and land use change emissions, the land and ocean sinks, and lastly, the growth in carbon dioxide concentration in the atmoshphere.

Secondly, we consider out-of-sample forecast performance by truncating the sample at year 2000 and using the model to forecast out the final 17 years and evalulating the forecasts against the realised values. Again, the RMSE is presented for the different models, with the RMSE being calculated only for the forecasted periods.

The models being compared are the baseline model (BL) and a naive forecast of the growth rate in carbon dioxide concentration in the atmosphere using a simple AR(1) model with linear and logarithmic trends.

| | $E^{FF}$ | $E^{LUC}$ | $S^L$ | $S^O$ | $G$ |
|---|---|---|---|---|---|
| BL | 0.4511 | 0.1441 | 0.8757 | 0.1428 | 0.9783 |
| AR(1)-Trend | - | - | - | - | 0.9420 |

Table 3: RMSE - Model Fit

Below, we present the fit for the three models for the growth in carbon dioxide concentration in the atmosphere.

| | $E^{FF}$ | $E^{LUC}$ | $S^{L}$ | $S^{O}$ | $G$ |
|---|---|---|---|---|---|
| BL | 0.3134 | 0.1021 | 0.7488 | 0.1178 | 0.8815 |
| AR(1)-Trend | - | - | - | - | 0.8417 |

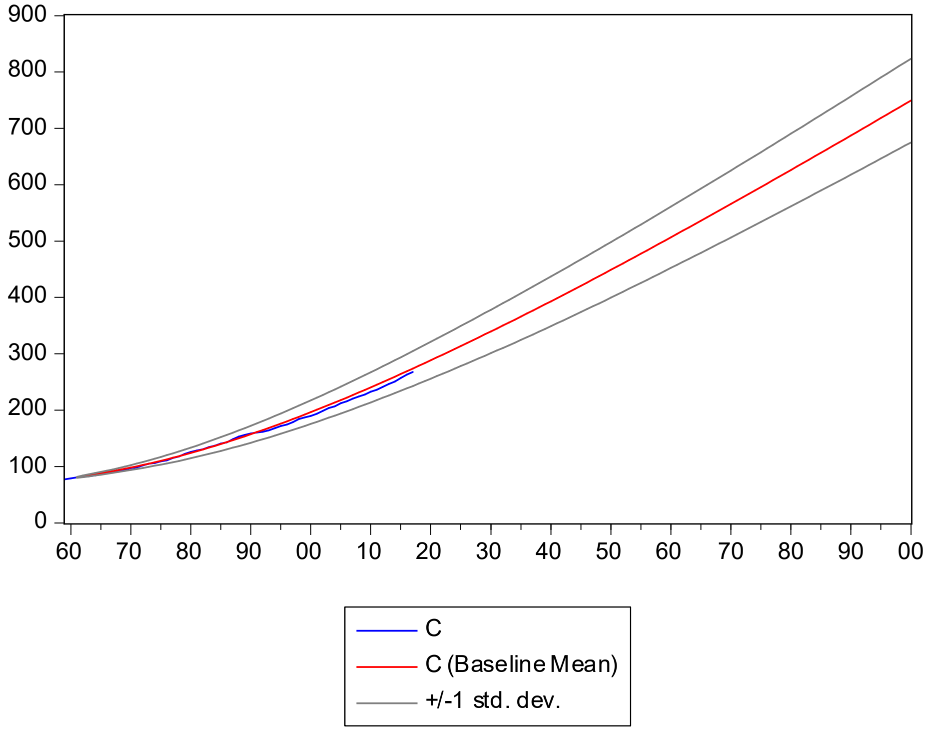
Table 4: RMSE - Out of Sample Forecasts

### 6.2 Model Projection to 2100

Below, we present the projections for the main components of the global carbon budget series to 2100 using our baseline model. Our model appears to fit the data on atmospheric carbon well (Figure 4). The upward trend in atmospheric carbon growth over 1959–2017 tapers off towards the end of the sample and begins to level out over the projection horizon. This reflects the balance between anthropological emissions and biosphere sinks, and is driven by the feedback of concentration levels on sinks (Figure 5). Our model suggests that as atmospheric carbon concentration increases, ocean and land sinks will tend to have a larger flux, sinking larger amounts of carbon each year. This is discussed further below.

Our model for fossil fuel emissions principally follows a linear trend. The path is suggestive of a potential structural break, or sustained deviation from the trend over 1980–2000; however, a Quandt-Andrews test finds no evidence of a break. The model for land use change is very naive as the data are volatile and show no clear trend. This component is a small share of emissions, so is unlikely to drive the results.

As mentioned, in figure 4 sink levels for both ocean and land are expected to increase in the future. This is a projection of the relationship we found between sink and atmospheric concentration level within the period of the data - as concentration climbs higher, so does the amount of carbon absorbed into the land and ocean. It is not clear how long we can project this relationship forwards: FRS Read (2001) predict that potential gains in land sink capacity through land-use change and halting deforestation have a limit. Note that the prediction for future land sink is much smoother than historic volatility level warrant.



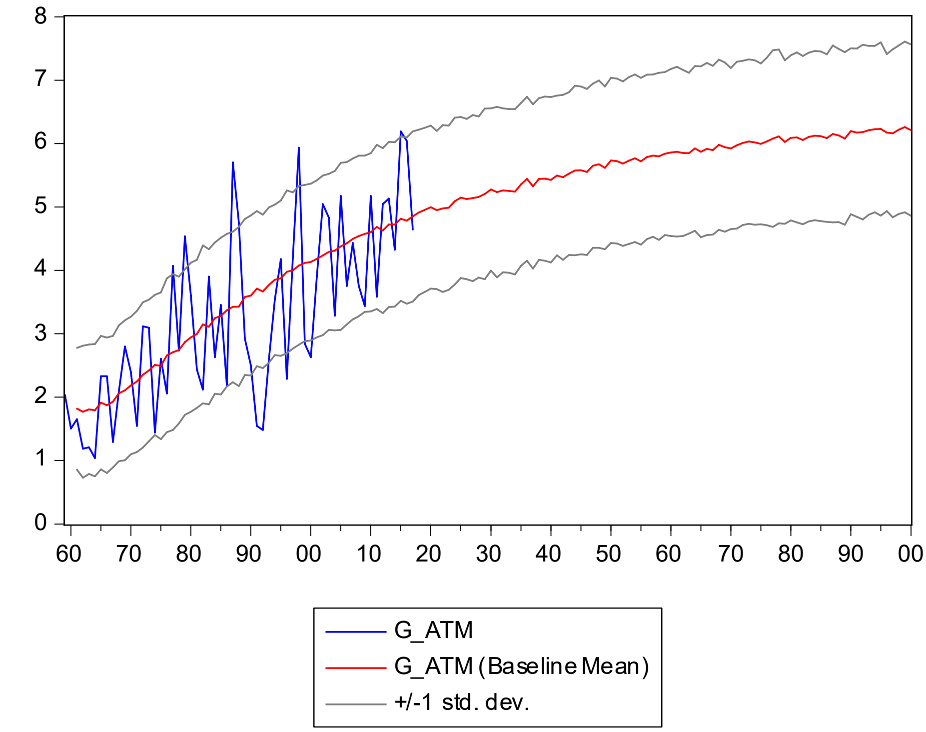




Figure 4: Atmospheric carbon concentration and growth, model fit and projections 1959–2100

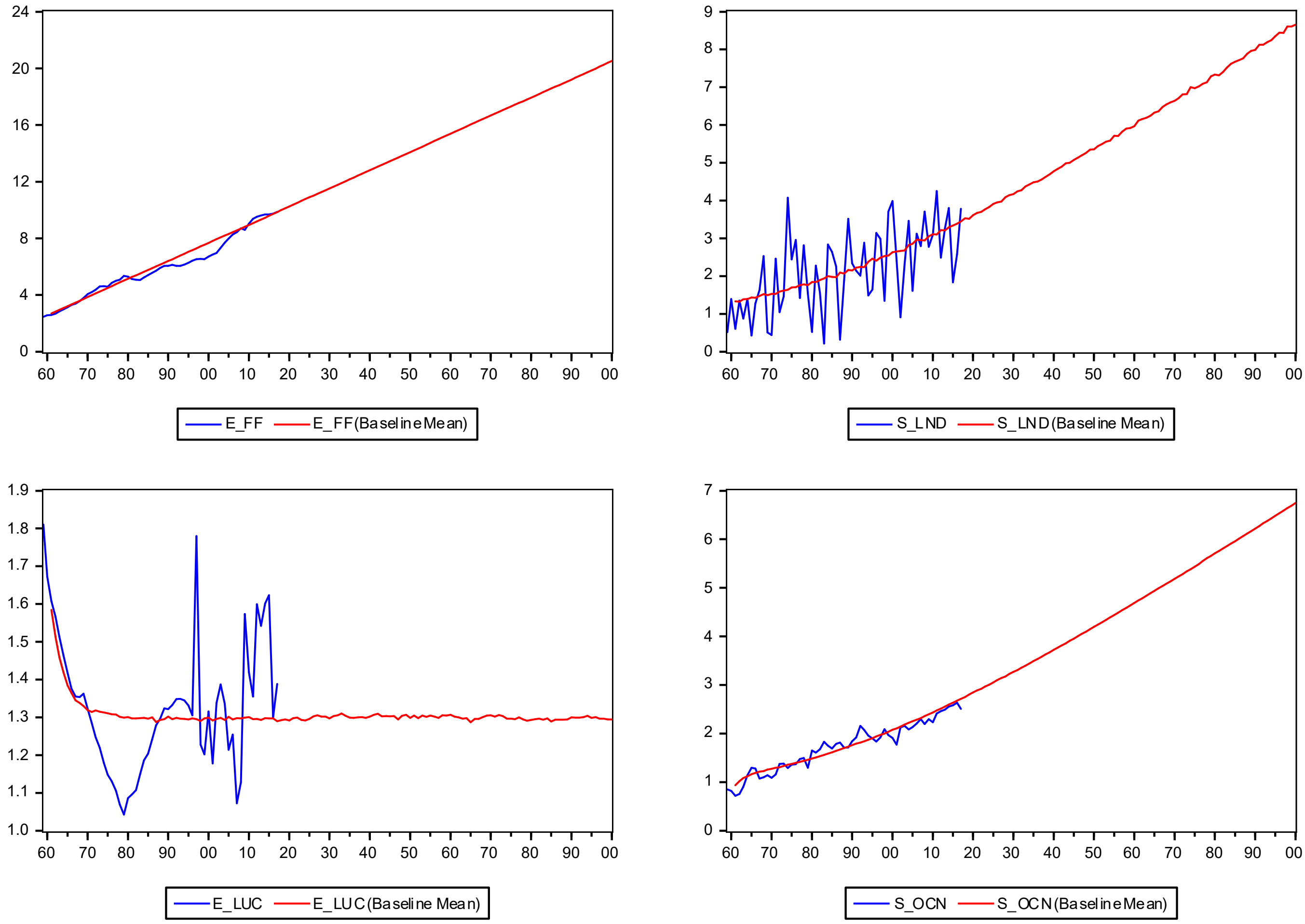



Figure 5: Anthropogenic emissions and biosphere sinks, model fit and projections 1959–2100

### 6.3 Examining the Feedback Mechanism

The feedback mechanism between concentration and biosphere sinks is a crucial determinant of the model projections and a subject of disagreement in the literature. Our estimates of the sink efficiencies are positive constants (Table 5). Raupach et al. (2014) and Bennedsen et al. (2018) find evidence for a decline in the efficiency over time, whereas Ballantyne et al. (2015) finds evidence for an increase. We test whether the efficiency parameter in our ocean sink model is time-varying by specifying a state space model whether the parameter is modelled as a latent variable following a random walk.

$$S_t^O = \beta_0^O + \mu_t^O C_{t-1} + \beta_2^O S_{t-1}^O + e_t^O$$

$$\mu_t^O = \mu_{t-1}^O + \epsilon_t^\mu$$

The maximisation procedure struggles to converge, particularly in estimating a variance for the state equation. This may suggest the model is not a suitable fit for the data. Filtered and smoothed state estimates are shown in the top panel of Figure 6. The smoothed estimate is constant, indicating that there is very little time variation. An alternative model that removes the autoregressive term from the specification is also tested – this shows more time-variation, but no economically meaningful trend. The results suggest that a constant sink efficiency is sufficient.[1]

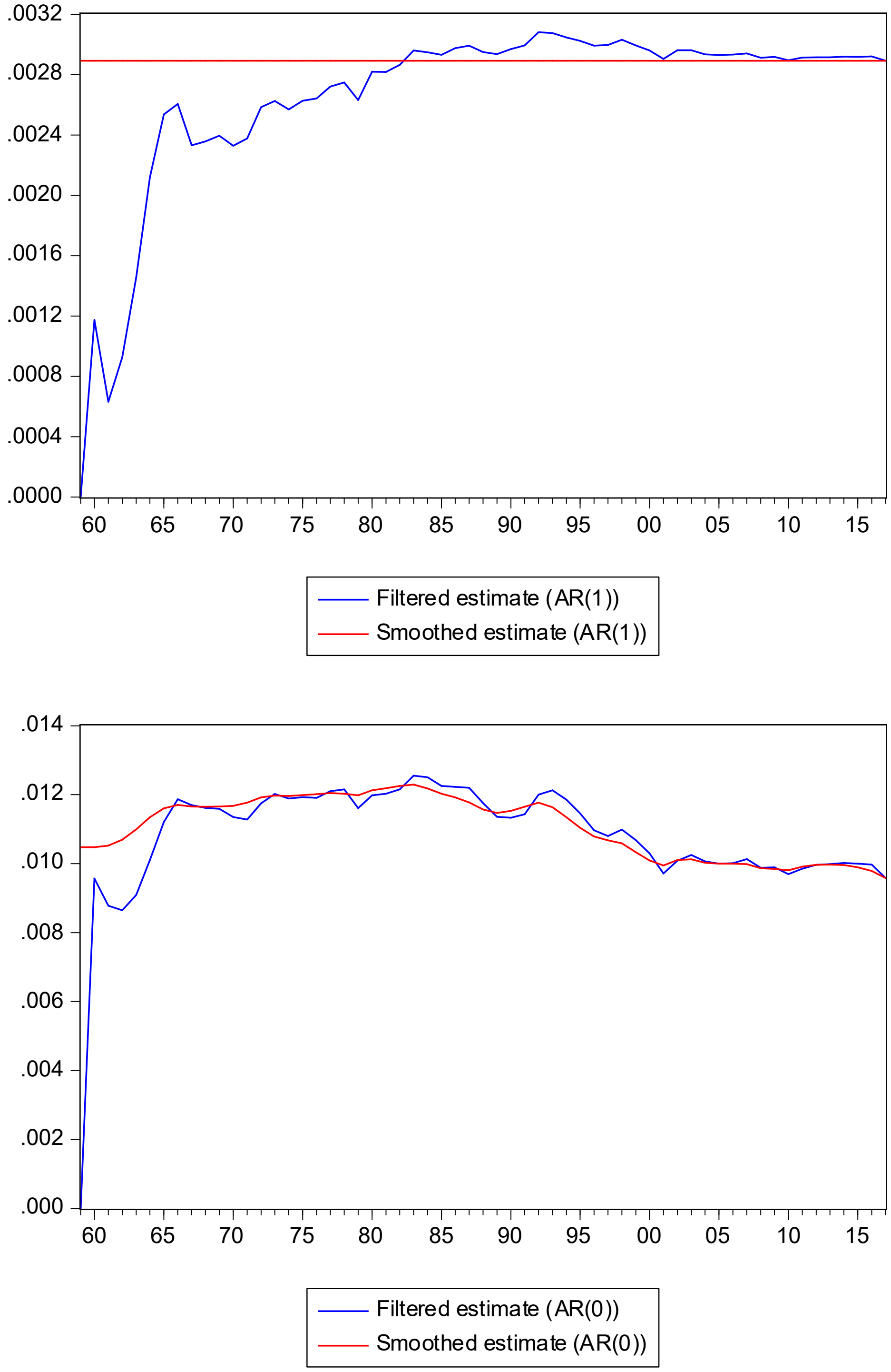



Figure 6: Time varying parameter estimates for ocean sink efficiency

Another possibility is that the sink efficiency is not a linear relationship. Our model assumes that carbon

[1]It should be noted that the literature considers this question much more thoroughly than we do here.

sink is increasing in concentration at all levels, whereas this may not be the case (FRS Read (2001)). Following the result in Raupach et al. (2014) – that a nonlinear response in ocean sink contributes markedly to their estimated reduction in sink efficiency – we consider nonlinearity in our ocean sink model by including a squared concentration term.

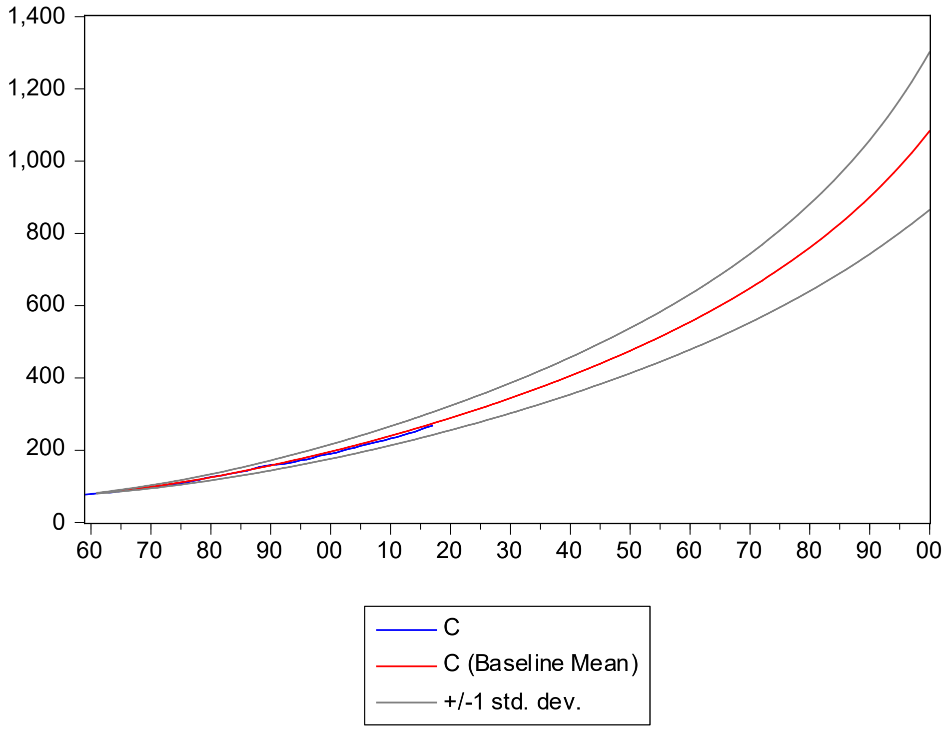
$$S_t^O = \beta_0^O + \beta_1^O C_{t-1} + \beta_2^O C_{t-1}^2 + \beta_3^O S_{t-1}^O + e_t^O$$

The coefficient is marginally statistically significant and very small. Nonetheless, this one change has large ramifications for the projections from our system. The negative coefficient on the squared concentration term attenuates the positive feedback over time, eventually turning it negative. This can be seen as a "tipping point" dynamic, whereby further climatic change results in an acceleration of the process. This statistical process mirrors the hypothesis that further carbon concentration leads to warmer temperatures and hence less ocean abatement.

The adjusted model now predicts upward curving carbon concentration levels and growth, in stark contrast to our baseline model (Figure 7). The projection for the ocean sink model clearly shows what drives this difference, with oceans beginning to *contribute to*, rather than subtract from, atmospheric carbon by 2070. The estimation of this quadratic term on a relatively short sample should be taken with caution, and clearly the prediction is hugely out of line with historical precedence. Nonetheless, the exercise illustrates the sensitivity of the model to assumptions, and the important role of the feedback mechanism.

| | Point Est. | Std. Err. | $t$-stat | $p$-value |
|---|---|---|---|---|
| $\beta_0^O$ | -0.0691 | 0.1355 | -0.5102 | 0.6119 |
| $\beta_1^O$ | 0.0076 | 0.0026 | 2.8794 | 0.0057 |
| $\beta_2^O$ | -1.1E-05 | 6.1E-06 | -1.8962 | 0.0633 |
| $\beta_3^O$ | 0.5587 | 0.1134 | 4.9230 | 0.0000 |

Table 5: Parameter Estimates



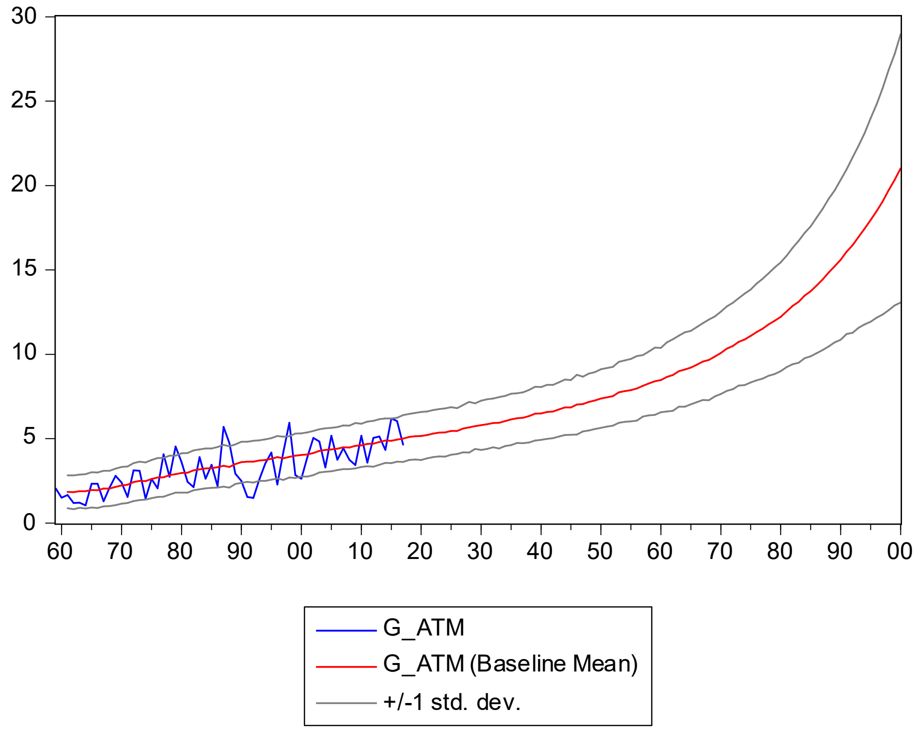




Figure 7: Atmospheric carbon concentration and growth, model fit and projections 1959–2100

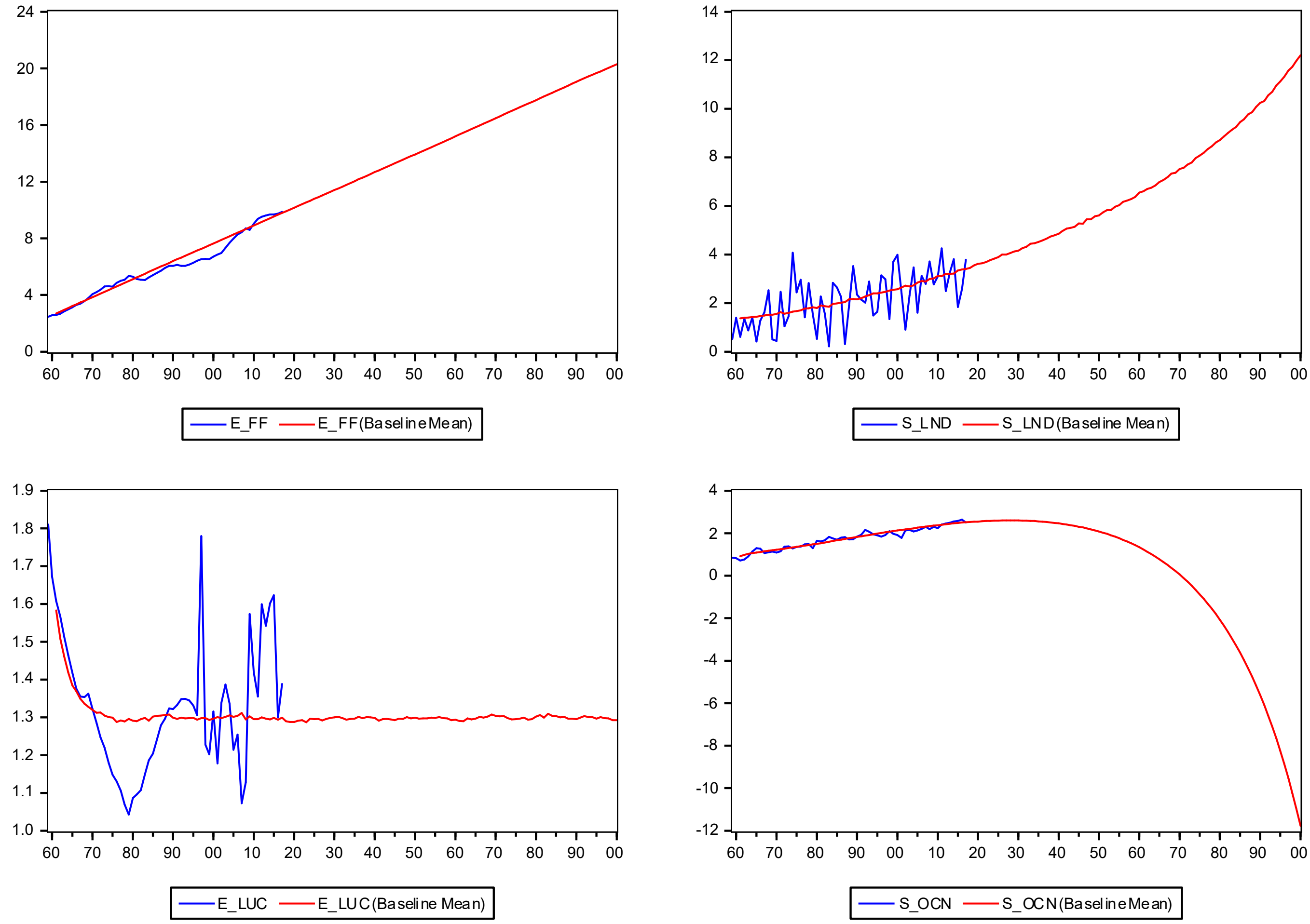



Figure 8: Anthropogenic emissions and biosphere sinks, model fit and projections 1959–2100

### 6.4 Representative Concentration Pathways Initiative Scenarios

The Representative Concentration Pathways (RCP) is a set of scenarios providing a range of possible projections of atmospheric conditions (Meinshausen et al. (2011)). They form part of an international project to compare climate model simulations and comprise four scenarios based on the predicted radiative forcing level:

- RCP2.6 is strong mitigation scenario where greenhouse gases are reduced substantially, resulting in a global mean surface temperature increase of 1.5°.
- RCP4.5 is a stabilisation scenario involving some reduction of greenhouse gas emissions utilising carbon capture technologies and emissions pricing.
- RCP6 is a scenario where radiative forcing stabilises at $6W/m^2$ with no prior overshoot and peak emissions around 2060.
- RCP8.5 is a high emissions scenario driven by population growth and slow technological change (due to weak climate change policies), resulting in a global mean surface temperature increase of

4.5°.

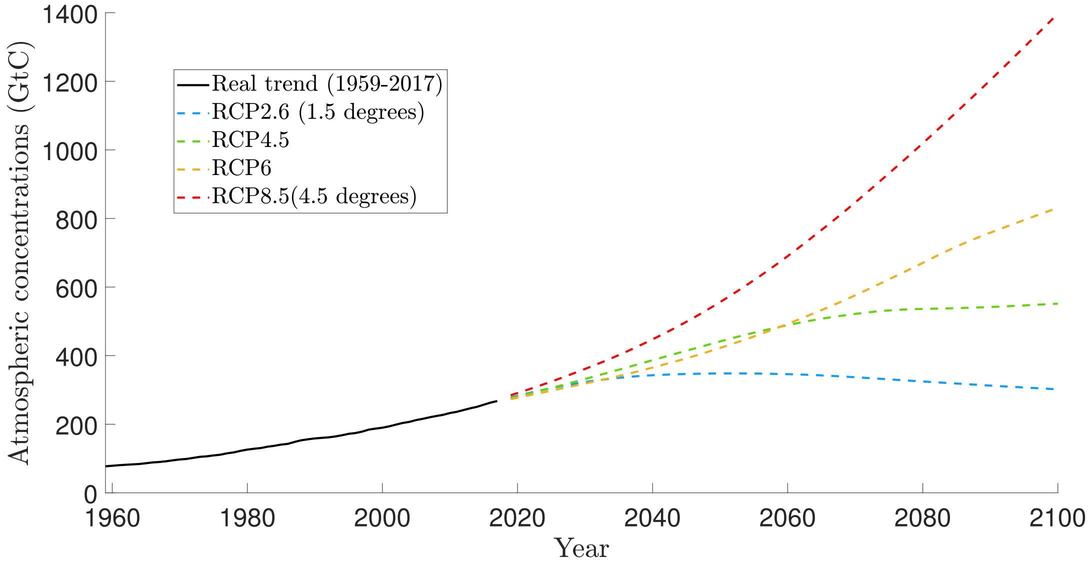



Figure 9: Real Trend (1959-2017) vs. Representative Concentration Pathways (2019-2100)

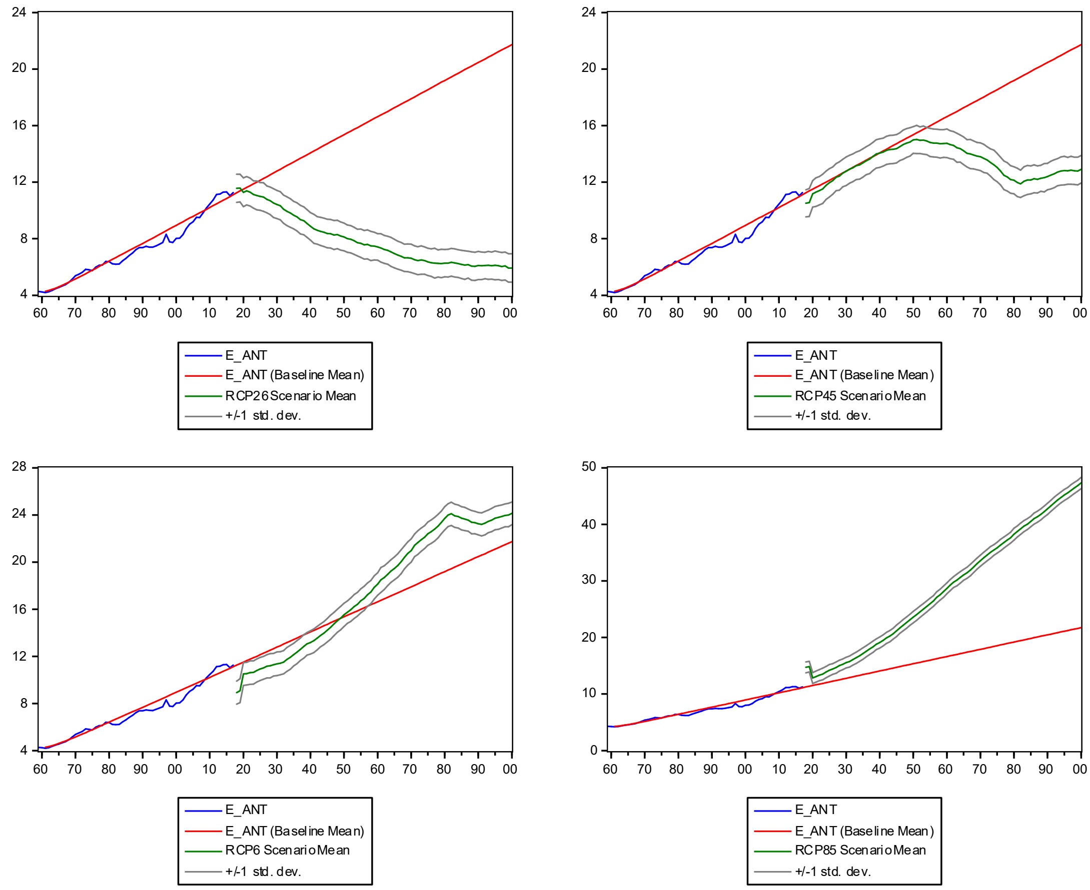



Figure 10: Forecast of future emission based on scenarios from Representative Concentration Pathways (2019-2100)

The RCP scenarios present strikingly different implications for future emission pathways. In the strictest one ($RCP2.6$), where mean global temperature is projected to increase by $1.5^oC$, the emission level needs to be sharply reduced - in fact, by 2100 the yearly emission level should be approaching 1960 - 1970 level (about 6 GtC / yr). This result is striking, considering the projected future growth of developing economies and the implied energy uses. This scenario will then required concerted political efforts to both bring down carbon emission level of developed countries and adopt non-carbon-intensive growth strategies in developing ones.

RCP 4.5 and 6.0 represents two intermediate scenarios, where emissions are not projected to be as substantially reduced. In the former case, emission can keep growing until around 2060, where it starts to trend downwards and stabilize near the 2017 level (roughly 12 GtC/yr). Though it does not require efforts as stringent as the RCP 2.6 scenario, stabilization of emission will still necessitate increased carbon capture, some carbon pricing scheme and further adoption of alternative energies. In comparison, RCP 6.0 is a closer fit with our projection of future emission path at the current growth rate. The scenario seems to imply a peak at around 2080 of 24 GtC / yr, though whether emission picks up again requires longer-horizon forecast.

RCP 8.5 sees the planet warms up by about $4.5^oC$ on average, representing a catastrophic scenario. In this situation, emission not only grow without bound in the future but accelerate. Though the path is above our model's prediction of future emission growth, it is not entirely impossible considering future growth prospect of developing economies. Moreover, recall that the scenario also assumes strong population growth and weak adoption of climate technology. With the US and the European Union currently distracted by political problems, and the world population projected to 11.2 billion in 2100 (UN, 2017), there are challenges ahead in averting this catastrophic possibility.

# 7 Discussion

This section focuses on the discussion of our key results, as well as comparisons with other forecasts of similar quantities in the literature. In general, our model predicts the following results as we forecast out to 2100.

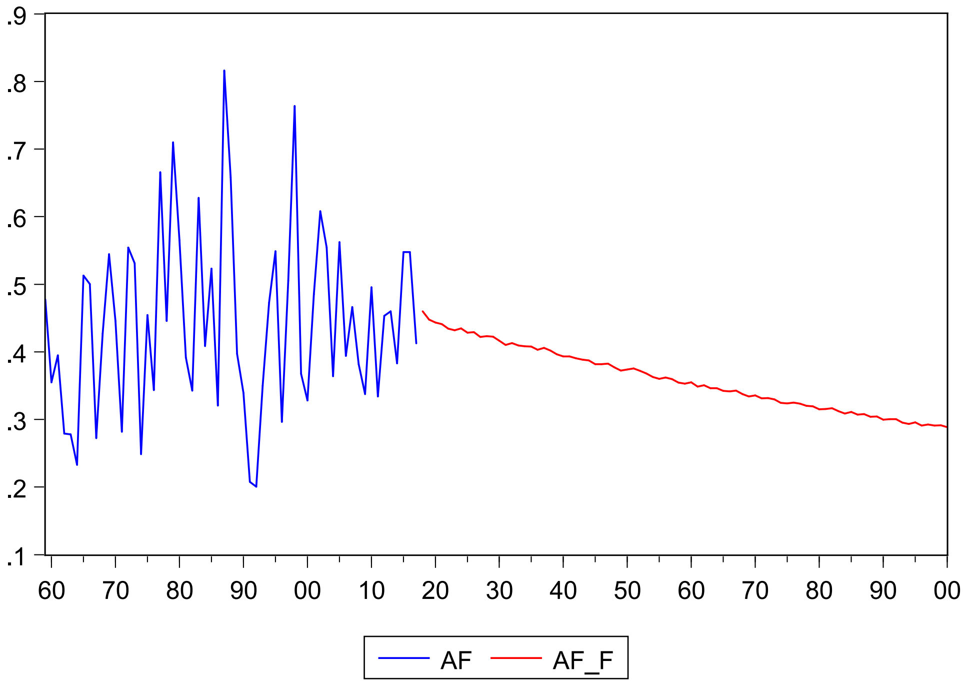
*Emissions from fossil fuels increase linearly into the future.* It is difficult to determine the accuracy of this forecast. Based on the AR(1) model for the growth of fossil fuel emissions, the long-run growth is given by

$$\Delta \tilde{E}^{FF}_{t+1} = \frac{\hat{\gamma}_0}{1-\hat{\gamma}_1} = \frac{0.087}{1-0.325} = 0.1289$$

Therefore, in 2017, the predicted growth *rate* is given by $0.1289/9.87 = 1.3\%$. Whilst this may be accurate on a long-run basis, The 2018 Global Carbon Project (GCP) (Le Quéré et al., 2018) notes that emissions from fossil fuel use increased at a record rate of 2.7% in 2018. There are several reasons why emissions grew at a much higher pace in 2018, most notable is the government stimulus in the construction sector in China (Le Quéré et al., 2018). It is difficult to evaluate whether 2018 demonstrated an anomaly or some form of long-run structural change. The increases in 2017 of 1.6% are much more similar to our forecasts.

It is important to keep in mind that forecasting over an 83 year horizon to 2100 carries significant risk, especially in the assumption that there will be little structural change. The lesson in regards to forecasting fossil fuel emissions seems to be that changes can be extremely volatile and public policy in major countries, such as China, can significantly alter forecasts. On the other hand, unlike emissions from fossil fuel use, emission from land use change is relatively small and is therefore much less important. Whilst the volatility in the series is high, there are appears to be no obvious trends or patterns, leading to a long-run average being the best possible forecast. With the rapid increase in fossil fuel emissions, the land use change emissions will become relatively less important over time.

*The land and ocean sinks are the greatest source of uncertainty in the model. However, we predict a decreasing airborne fraction.* The fraction of emissions which remain in the atmosphere, the aforementioned airborne fraction, can be highly variable year to year. In the following figure, we present the airborne fraction from 1959 to 2017, then, the subsequent forecasted airborne fraction until 2100.




This graph is noteable for two reasons. Firstly, it demonstrates the volatility of the airborne fraction, and secondly, it predicts that the airborne fraction is trending downwards over time. This is potentially at odds with the current research, e.g. Le Quéré et al. (2009). Their findings suggest that the airborne fraction increased on average 0.3% per year between 1959 and 2008, with 90% certainty that the increasing trend is significant. Furthermore, they conclude that a positive trend in the airborne fraction is likely, with 66% confidence. Despite this evidence, there would be reason to believe the airborne fraction should be trending upwards. Denman et al. (2007) suggests that there are limits to carbon dioxide fertilisation in both land and ocean sinks, and the efficiency of such processes decrease at higher ambient carbon dioxide concentrations. Furthermore, it is possible that the land and/or ocean carbon dioxide sink may be responding to temperatures directly, which is not exogenously taken into account in our model.

Furthermore, it is suggested that, whilst the long term proportion of carbon dioxide taken up by the ocean cannot be measured directly, a weakening of regional carbon dioxide sinks have been observed since at least 1990. Despite scientific arguments, the model-based airborne fraction trend was estimated to be decreasing at a rate of 0.8% per year which supports our results. It is noted that the change is highly uncertain. This is not very different from the long-run decrease in the airborne fraction in our model, which averages a decrease of 0.6% over the years from 2017 to 2100. Since the decrease is non-linear, we take a geometric average by

$$r = \left(\frac{AF_{2100}}{AF_{2017}}\right)^{\frac{1}{83}} - 1$$

*The growth rate in the carbon concentration in the atmosphere is increasing at a sub-linear rate.* Our prediction of the growth in carbon concentration in the atmosphere shows that it is increasing at a decreasing rate. However, over the long horizon, it does seem that the growth is approaching a steady state.

# 8 Conclusion

Given the crucial role carbon dioxide plays in greenhouse effect, and the well-documented man-made effects of anthropogenic emission on rising carbon concentration, we are interested in understanding how future carbon concentration and emission look like. Though fossil fuel and land-use change carbon emission could be captured by land, the ocean or the atmosphere, the former two processes can be overwhelmed by increasing man-made emission.

In this paper we develop a statistical model to project anthropogenic emissions, sinks and atmospheric carbon concentration to 2100 and compare these with scenarios from the Representative Concentration Pathways initiative. The model was constructed based on the Global Carbon Budget Equation, with time series data from Le Quéré et al. (2018). Crucially, we predict land and ocean sink amount by their in-data statistical relationship with atmospheric concentration. This key assumption drives much of our results.

The RCP scenarios provide an interesting opportunity to evaluate our model, with different atmospheric concentration possibilities from 2019 to 2100 implying different underlying anthropogenic emission pathways. Our model backs out four different emission trajectories based on the four scenarios: for the situation with the lowest temperature change ($+1.5^oC$), emissions not only have to stop rising, they have to decline down to about the 1960-1970 level by 2100. This is in line with Meinshausen et al. (2011)'s description, being the case where there must be strong adoption of climate technologies and policies. In the opposite direction, the catastrophic scenario with $+4.5^oC$ change comes from emission increasing at an even higher rate than the current one. This out of control growth is projected to accompany weak climate policies, and strong population growth. The current trends points towards the intermediate scenario, however, projection over such a long horizon should be taken with some skepticism.

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