How to save the planet? A state space model approach

Team 1

Abstract

Climate change is nowadays a key topic of interest in political discussions. It is crucial to have proper models and perform accurate forecasts of climate-related variables to efficiently tackle the issues that climate change brings. This paper focuses on two aspects: the sensitivity of global CO2 atmospheric concentration forecasts to changes in CO2 emissions in different regions of the world and how such changes in emissions can be achieved. We propose a state space approach that takes into account the measurement errors to which climate data is subject. The model is based on the Global Carbon Budget Equation and allows to jointly estimate and forecast all the unobserved components driving the observed variables of the Budget Equation and CO2 atmospheric concentrations. It also has the flexibility to model the CO2 emissions for a group of countries. We further extend the state space model in order to allow the latter emissions to depend on an indicator of economic activity for the region investigated. We compare our forecast from 2019 to 2100 to Representative Concentration Pathways (RCP) that correspond to distinct scenarios leading to different temperature increases above pre-industrial levels. We find that a decrease in the EU28 CO2 emissions seems to have a bigger impact in reducing future CO2 concentration than changes in the US or non-OECD CO2 emissions. While we do not find a significant difference between the effects of CO2 emission changes for developed and developing countries, a limitation may arise with respect to rooms for policies in the latter. Furthermore, focusing on the US, our model indicates that CO2 emissions react positively with a magnitude 3 times higher than the change in production. It suggests that, given all external factors constant, CO2 emissions could be reduced by a half by 2040 if production was gradually decreased by 2.5% per yer, hence, without harming economic activity.

Keywords: Global Carbon Budget Equation, CO2 Atmospheric Concentration, State Space Models, Forecasting, Territorial Emissions, Economic Activity.

Contents

1 Introduction

Over the last two decades, the Carbon Budget has been a problem of great interest, especially after the Earth Summit in Rio de Janeiro in 1992, where the member states of the United Nations decided to stick together to handle the conflict relating to sustainability and global warming. Awareness regarding climate change increased and it became clear that the need for understanding the relationship between carbon dioxide (hereafter CO2) emissions, land and ocean sinks and CO2 atmospheric growth is critical. The problems were again emphasized at the COP21 in Paris, at which present States agreed to keep the global temperature increase below 2 degrees above pre-industrial level. However, unlike its predecessor, the Kyoto Protocol, which sets commitment targets that have legal force, the Paris Agreement, with its emphasis on consensus-building, allows for voluntary and nationally determined targets. The specific climate goals are thus politically encouraged, rather than legally bound. Climate change is however a global matter and the actions of one country clearly have worldwide repercussions. To efficiently tackle global warming, new policies need to be established, and most importantly, policies between countries need to be aligned. Hence, not only is it essential to understand historical and recent climate variations, it is also necessary to perform reliable forecasts to compare potential future scenarios of various environmental variables, globally and across countries.

The growth rate of atmospheric CO2 is the largest human contributor to human-induced climate change and it is increasing rapidly. It is crucial to have a proper understanding of the global carbon cycle and to have accurate measurements of CO2 emissions and their redistribution among the atmosphere, ocean, and terrestrial biospheres. The carbon cycle implies that the amount of emitted CO2 that is not absorbed by the land or the ocean sinks must end up in the atmosphere. Hence, the equilibrium condition is as such,

$$G_t = E_t^{FF} + E_t^{LU} - S_t^{LD} - S_t^{OC},$$

where G_t is the growth in atmospheric CO2 concentration, E_t^{FF} are CO2 emissions from fossil fuels combustion and industrial processes, E_t^{LU} are the CO2 emissions from land-use change (e.g. deforestation), S_t^{LD} is how much of these emissions are absorbed by the terrestrial biosphere and S_t^{OC} is the amount absorbed by oceans (Le Quéré et al., 2018). However, each variable is measured from different environmental models and the construction of each variable is hence subject to measurement errors. In practice, this leads to a significant discrepancy between the right and left hand sides of the identity, implying a disequilibrium in the carbon cycle. The Global Carbon Project aims at quantifying this discrepancy (denoted by ε_t) by means of the so called Global Carbon Budget Equation,

$$G_t = E_t^{FF} + E_t^{LU} - S_t^{LD} - S_t^{OC} + \varepsilon_t. \tag{1}$$

It is however impossible to disentangle whether a positive imbalance for instance is induced by an overestimation of emissions, an underestimation of the sinks absorption or an overestimation of the growth of atmospheric CO2 concentration.

The rise of interdisciplinary techniques and mostly the use of econometric methods have been of interest in the recent years as similar problems have been observed in economic applications.

The aim of this paper is to model the sensitivity of global CO2 atmospheric concentration forecasts to changes in CO2 emissions in different regions of the world and how such changes in emissions can be achieved, by means of an econometric approach. We propose a state space model that takes into account the measurement errors to which climate data is subject. It is built upon the Global Carbon Budget Equation. It allows to jointly estimate and forecast the state variables of all the observable variables that appear in the Carbon Budget Equation as well as the CO2 atmospheric concentrations. We divide worldwide emissions into a region's emissions and that of the rest of the world, to investigate the individual effects on global CO2 atmospheric concentration of such region. We further extend the state space model in order to allow the regional CO2 emissions to depend on an indicator of economic activity for the region investigated.

The paper is organized as follows, Section 2 highlights the motivations and the necessity of an econometric model for the Carbon Budget that incorporates the individual effects of the emissions of specific countries or groups of countries. Then, the paper describes the data set used in this research. Section 4 presents the construction of the state-space model based on the Global Carbon Budget. Estimation of the model between 1959 and 2017, forecasts up to 2100 and a sensitivity analysis that considers the individual country effects and the relation between US emissions and the production index are performed in Section 5. Section 6 discusses the limitations and the possible further research that this paper sheds light on, before concluding in Section 7.

2 The Global Carbon Budget and territorial emissions

The Global Carbon Budget states that all CO2 emissions must either end up in the Earth's sinks or in the atmosphere, while accounting for potential measurement errors. The traditional approach to model the growth of atmospheric CO2 concentration has been related to the field of physics and climatology (Le Quéré et al., 2018). Each variable in the Budget Equation (1) is measured with distinct – usually – climatology models and the imbalance is then simply constructed as the discrepancy between the measured atmospheric CO2 concentration growth and the one implied by the difference between emissions and Earth absorption.

Measurements errors associated with CO2 measurements and emission estimates still limit our confidence in calculating net carbon uptake from the atmosphere by the land and ocean (Ballantyne et al., 2015). As we enter into an era in which scientists are expected to provide an increasingly more detailed assessment of carbon concentrations in the atmosphere at increasingly higher spatial and temporal resolutions (Canadell et al., 2011), it is critical that we develop a framework less influenced by these measurement errors. Therefore, instead of solely relying on the budget equation and estimating each series separately to approximate the imbalance, the equation now builds the backbone of the statistical models used to predict the concentration level of CO2. Several approaches have been undertaken recently in the field to model the CO2 concentration. Strassmann and Joos (2018) suggest a simple climate model, known as Bern Simple-Climate model (BernSCM), in order to capture the carbon cycle appropriately and measure the long-term effect of humans in the Earth's Budget Balance but they do not tackle the issue of measurement errors. The model links a climate component with an energy-economy model to simulate the emissions and corresponding consequences for the climate. Bennedsen et al. (nd) on the other hand recognize the problem of measurement errors that occur with estimating the carbon concentration by modelling the airborne fraction and sink rate of CO2 released by human force in a state space model. Such models are based on the assumption that the variable of interest is mis-measured and that it is therefore unobserved. The authors present several ways to measure the impact of human behavior in the Earth's energy budget by using the Budget Equation as a part of the model construction.

Another concern with respect to modelling the global carbon cycle is the potential feedback effect between CO2 atmospheric concentration and climate change. Indeed, we expect an increase in CO2 concentration to lead to an increase in temperature, which may then lead to a reduction in land and ocean absorption (more arid soils or more water evaporation for instance). In the literature, this topic is widely discussed among scientists. However, no agreement has been found about the existence or the magnitude of such feedback effect. Among others, Friedlingstein (2015) compares eleven coupled climate-carbon models and while they find significant feedback effects, no consensus is found regarding the magnitude of such feedback or even to what it is attributed. Strassmann and Joos (2018) find that the significance range of the feedback includes zero while Gloor et al. (2010) attributes the significant findings to omitted variables or inadequate analysis of the data. For the sake of simplicity and from the lack of consensus regarding this feedback effect, we will assume that it is non-existent and will therefore omit it in the model construction.

Moreover, the paper aims to stress the fact that each and every nation affects the global climate. Where the Paris Agreement failed in 2015 to reduce carbon emissions based on multilaterally negotiated binding country-specific targets, we highlight the necessity of a multilateral cooperation. As discussed in Clémençon (2016), nations have shown their own interests and positions in the climate discussion. India, with per capita CO2 emissions of 1.5 tons, maintains the opinion that rich countries must pay back their historic debt. Conversely, China, with per capita CO2 emissions of 6 tons, has a decreasing interest in a sharp differentiation between countries based on per capita and historic emissions. An interesting topic is to evaluate what the impact is of a specific country on the Carbon Budget and the differences of the effects of countries, depending on their level of development.

The aim of this paper is to construct an econometric model to investigate the individual effects of a country or group of countries on the CO2 concentration. To cope with all the above named concerns, we will employ a state-space model inspired by Bennedsen et al. (nd) that can manage individual effects of countries of groups of countries.

3 Data

For this research, we use a data set provided by http://www.icos-cp.eu/GCP/2018 which contains yearly time series data from 1959 to 2017, amounting to 59 observations. The data objects are anthropogenic carbon emissions from fossil fuels and cement production emissions (E^{FF}) and from land-use change, mostly deforestation and afforestation (E^{LU}) , different estimates of how much of these emissions are absorbed by the terrestrial biosphere (land sink, S^{LD}), and different estimates of the amount absorbed by the ocean (ocean sink, S^{OC}). By necessity, all emissions not absorbed by Earth's carbon sinks must end up in the atmosphere, and so the final object of interest is the growth in atmospheric concentrations (G). All observables are measured in billion tonnes of carbon per year (GtC/yr). Furthermore, we use a data set provided by the Global Carbon Project (Le Quéré et al., 2018). It provides CO2 emissions in million tons of carbon per year for 213 countries and territories. For this research we are interested in the effect what a particular country or group of countries has on the global CO2 concentration. We decide to consider the United States (US), European Union (EU28) and non-OECD countries as variables of interest. Then we obtain the observed variables E^x, for x = US, EU28, non-OECD. Then we will use the combined variables sink ($S^{LD} + S^{OC}$) and total global emission without the emission of country x, so $E^R = E^{FF} + E^{LU} - E^x$. The reasoning behind this will be further elaborated in the next section. Furthermore, we aim to capture a connection between emissions of a country and a broad indicator of economic activity of that country. For that we use the industrial production index (I) provided by https://fred.stlouisfed.org/series/INDPRO. We decided to focus on the connection between this index and the emission for the US. This data set consists of monthly seasonally adjusted data from 1959 until 2017 with the index at 2012 equal to 100. We aggregate the data from monthly to yearly data by taking the average of the months in a year. The plots of atmospheric growth, emission of country x, total global emission without the emission of country x, sink and the production index in levels and in differences are given in the Appendix (Figure 15 to 23). Furthermore a summary statistics table for these variables is given in the Appendix (Table 4 and 5).

Next, we continue the analysis by formally testing for unit roots in the series. In particular, we want to identify the order of integration of our series. In this context, one should address the concept of the Pantula Principle, which is especially relevant for the Augmented Dickey-Fuller (ADF) test. One should difference the series as many times as it deems appropriate for making the series stationary, which we specify to be $d = 2$. We test for a unit root in the differenced series. If the null of a unit root is rejected, we decrease d by one and repeat the unit root test. The procedure is stopped when the test cannot be rejected anymore. The order of integration is then assumed to be $I(d+1)$. This procedure ensures that the differenced lags included in the ADF test are stationary. The following table depicts the results from the ADF test, where the null hypothesis is non-stationarity and the alternative hypothesis is stationarity. From this we can conclude that the emission without non-OECD, sink, the EU28 emission and the production index series are integrated of order one and that atmospheric growth is stationary in levels. The remaining series are then integrated of order 2. However, for all of them except emission non-OECD, we just accept the null with a 5% test size. Considering the graphs in the Appendix, we would expect all series except non-OECD to be $I(1)$. The reason that the ADF test gives different results can be due to the small sample size, since we only have 59 observations. Therefore, we rely on what the graphs tell us and conclude that all those series are integrated of order one. For the emission non-OECD series we will assume it is of order one as well, for simplicity reasons.

Since the CO2 atmospheric concentration is the variable of interest, we construct this variable in the following way,

$$C_t = C_{1959} + \sum_{\tau=1}^{t} G_\tau, \tag{2}$$

where C_t is measured in GtC/yr.

	Atmospheric Growth	Emission without US	Emission without EU28	Emission without Non-OECD	Sink
2nd difference	0.01	0.01	0.01	0.01	0.01
1st difference	0.01	0.05795	0.06411	0.01	0.01
Levels	0.03667	0.6261	0.6272	0.3667	0.06508

Table 1: p-values for the Augmented Dickey-Fuller test for stationarity

	Emission US	Emission EU28	Emission Non-OECD	Production Index
2nd difference	0.01	0.01	0.01	0.01
1st difference	0.06797	0.01	0.4258	0.01
Levels	0.7321	0.4948	0.6264	0.5622

Table 2: p-values for the Augmented Dickey-Fuller test for stationarity per group/separate countries

The previously discussed order of integration of the variables will be used in the construction of the model in the upcoming section.

4 A state space model approach

State space models allow to model variables of interest that are subject to measurement errors, which is the case for the Global Carbon Budget Equation, as the budget imbalance is generally different from zero. A state space model for the airborne fraction and the sink rate has already been proposed by Bennedsen et al. (nd). They model the trends of the above-mentioned variables in two different state space models. We build on their approach by proposing a single state space model that exploits the restrictions of the Global Carbon Budget Equation and jointly estimates the unobserved components of all the variables that appear in the equation. The available sample size and the order of integration of each series limit estimations when the number of parameters becomes too large. This paper focuses on the effects of territorial emissions paths of three regions (namely, the US, the European Union and the non-OECD countries) on global CO2 atmospheric concentration. Therefore, since no distinctions between the other sources of emissions and between the two sources of absorption are made, we make the following adjustments to the Global Carbon Budget Equation,

$$G_t = E_t^x + E_t^R - S_t + \varepsilon_t,$$

where E_t^x is the territorial emission of region x, $E_t^R = E_t^{FF} + E_t^{LU} - E_t^x$ is the fossil fuels and cement production emissions of the rest of the world, $S_t = S_t^{LD} + S_t^{OC}$ and $G_t = C_t - C_{t-1}$. We only investigate one region at a time to limit uncertainty induced by large number of parameters estimations. Global CO2 atmospheric concentration, C_t, our variable of interest is also included in the state space setting allowing us to directly estimate and forecast its state variable. State space models take the following form:

$$y_t = Z\mu_t + \epsilon_t \tag{3}$$

$$\mu_t = T\mu_{t-1} + M\eta_t \tag{4}$$

Equation (3) represents the observation equation, that is, we observe variable y but the variable of interest is its state, μ, which is not observed. The error term in the observation equation hence represents the measurement error in the observed variable. The transition equation (4), represents underlying dynamics of the variables of interest.

Global CO2 atmospheric concentration growth (G_t) can on the one hand be measured from environmental models, but can also be approximated by the difference between total emissions and absorption ($E_t^x + E_t^R - S_t$). That is, with different measurement errors, G_t and ($E_t^x + E_t^R - S_t$) should have the same state variable in the observation equations. Following the structure of Equation (3) and the assumptions made, we extend the basic example with our set of variables, leading to the following observation equations,

$$\begin{bmatrix} C_t \\ G_t \\ E_t^R + E_t^x - S_t \\ E_t^R \\ S_t \\ E_t^x \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 1 \\ 0 & 1 & -1 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_t^C \\ \mu_t^R \\ \mu_t^S \\ \mu_t^x \end{bmatrix} + \epsilon_t, \tag{5}$$

where ϵ_t is a vector stacking the six error terms of the observation equations, they are assumed independently normally distributed with mean zero and distinct variance: $\epsilon_t \sim N(0, H)$, $H = \mathrm{diag}(\sigma_{C,\epsilon}^2, \sigma_{G,\epsilon}^2, \sigma_{R+x-S,\epsilon}^2, \sigma_{R,\epsilon}^2, \sigma_{S,\epsilon}^2, \sigma_{x,\epsilon}^2)$. The CO2 atmospheric concentration variable is *I(2)* and its first difference is equal to G_t, which is *I(1)* and depends on the states of E_t^R, E_t^x and S_t which are themselves *I(1)*, as explained in Section 3. Hence, the state variables are assumed to be integrated of the same order as their corresponding observed variables and the transition equations of the four states of interest are as follows,

$$\begin{bmatrix} \mu_t^C \\ \mu_t^R \\ \mu_t^S \\ \mu_t^x \end{bmatrix} = \begin{bmatrix} 1 & 1 & -1 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1}^C \\ \mu_{t-1}^R \\ \mu_{t-1}^S \\ \mu_{t-1}^x \end{bmatrix} + \eta_t. \tag{6}$$

The four error terms η_t are also assumed independently normally distributed with mean zero and distinct variance: $\eta_t \sim N(0, Q)$, $Q = \mathrm{diag}(\sigma_{C,\eta}^2, \sigma_{R,\eta}^2, \sigma_{S,\eta}^2, \sigma_{x,\eta}^2)$. The matrix M from Equation (4) is equal to the identity matrix.

The hyperparameters of the model described above, i.e., all the variances of the error terms, are estimated by maximizing the following diffuse log-likelihood,

$$\ell_d = -\frac{Tn}{2}\log(2\pi) - \frac{1}{2}\sum_{t=d+1}^{T} \log\left(|F_t|\right) - \frac{1}{2} v_t' F_t^{-1} v_t,$$

where d is the number of non-stationary variables, and v_t and F_t are, respectively, the prediction errors and their covariance matrix. The latter are estimated, together with the state variables and their covariance matrices, via the Kalman filter recursions,

$$
\begin{aligned}
v_t &= y_t - Za_t \\
F_t &= ZP_tZ' + H \\
K_t &= TP_tZ'F_t^{-1} \\
a_{t|t} &= a_t + P_tZ'F_t^{-1}v_t
\end{aligned}
\qquad
\begin{aligned}
P_{t|t} &= P_t - P_tZ'F_t^{-1}ZP_t \\
a_{t+1} &= Ta_t + K_tv_t \\
P_{t+1} &= TP_t\,(T - K_tZ)' + Q,
\end{aligned}
$$

with $t = 1, \ldots, T$. We use a diffuse initialization for all the state variables, as all of them are non-stationary (Durbin and Koopman, 2012).

5 Results

5.1 Estimation

We estimate our proposed state space model for the sample period starting in 1959 and ending in 2017. Figures 1, 2 and 3 report, respectively, the filtered estimates of the state variables μ_t^C for C_t, $\mu_t^R + \mu_t^x - \mu_t^S$ of G_t and μ_t^x of E_t^x, when x = US, together with their 95% confidence intervals, which are constructed using the estimates for $P_{t|t}$ from the Kalman filter recursions. The figures show that the adequacy of the restriction on the state variable of G_t being equal to the one of $E_t^R + E_t^x - S_t$, as the estimated local trend, does not deviate much from the observed series G_t. On the contrary, the occasional deviations of the estimated trend from $E_t^R + E_t^x - S_t$ are due to a deterioration of the model when imposing a common trend (Bennedsen et al., nd). We do not venture into diagnostic checking as our main interest relies on the forecast of the state variables, rather than on a correct model specification. For the same reason we do not use Kalman filtering instead of smoothing.

5.2 Forecasts scenarios

Scientists have already performed several in-depth analyses of how the CO2 concentration would evolve when different restrictions are imposed over a forecast horizon until 2100. This set of scenario forecasts of the atmospheric greenhouse gas concentrations are called Representative Concentration Pathways (RCPs). For each category of emissions (for instance, agricultural emissions and aviation emissions), an RCP contains a set of starting values and the estimated emissions up to the year 2100, based on assumptions about economic activity, energy sources, population growth and other socio-economic factors (Moss et al., 2010). We consider four of these pathways: RCP8.5, RCP6, RCP4.5 and RCP2.6. Table 3 specifies the details of each path. Radioactive forcing measures the influence of a factor in the change of the Earth's energy balance (in watt per square meters). The goal of working with these different scenarios is not to predict the future but to better understand uncertainties and alternative futures. In this way, it is easy to derive how robust different political decisions or options may be under a range of possible futures. In order to explore what the RCP concentration scenarios imply for our forecasted emission paths, we use the RCP data set obtained from http://www.iiasa.ac.at/web-apps/tnt/RcpDb/. We have 82 observations, starting from 2019 up to 2100. Note here that the values provided in this data set are slightly lower than the ones indicated for the CO2 concentration in Table 3. We are going plot the RCP CO2 concentration

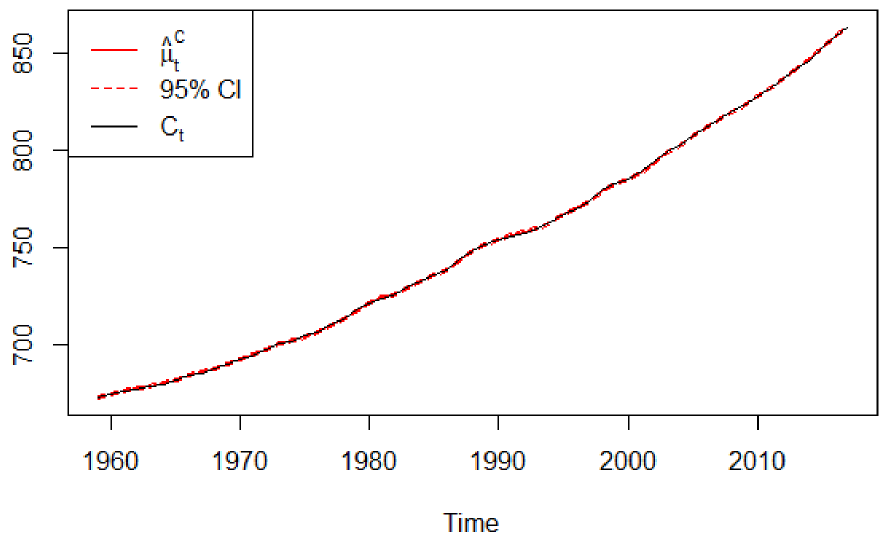

Figure 1: In-sample estimates of the state variable μ_t^C of C_t in GtC/yr, when x = US, together with their 95% confidence intervals.

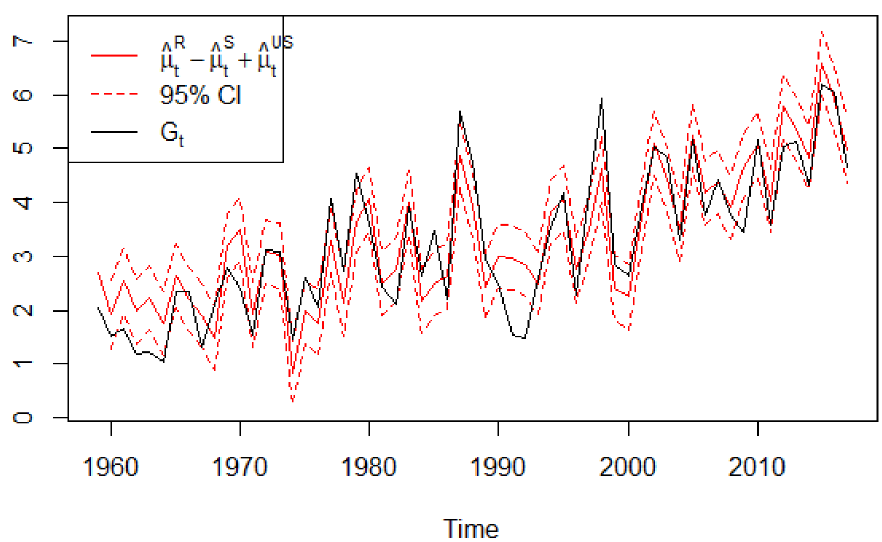

Figure 2: In-sample estimates of the state variable $\mu_t^R + \mu_t^x - \mu_t^S$ of G_t in GtC/yr, when x = US, together with their 95% confidence intervals.

paths for the four scenarios together with our forecasted series of CO2 concentration.

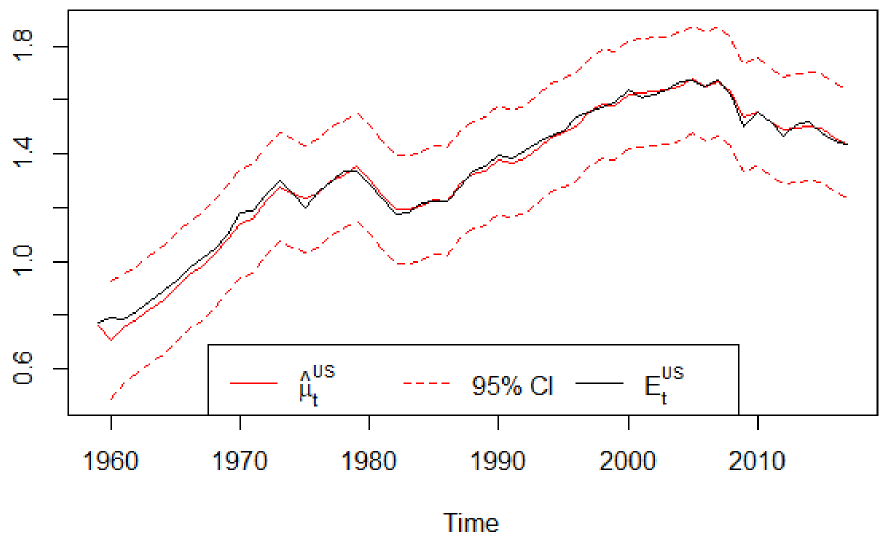

Figure 3: In-sample estimates of the state variable μ_t^x of E_t^x in GtC/yr, when x = US, together with their 95% confidence intervals.

Name	**Radiative Forcing**	**CO2 Concentration (in ppm)**	**Temperature Anomaly**	**Pathway**
RCP8.5	8.5 Wm^2 in 2100	1370	4.9	Rising
RCP6	6 Wm^2 post 2100	850	3	Stabilization without overshoot
RCP4.5	4.5 Wm^2 post 2100	650	2.4	Stabilization without overshoot
RCP2.6	3 Wm^2 before 2100, declining to $6Wm^2$ 2100	490	1.5	Peak and decline

Table 3: RCP-Scenarios Explanation

We based our forecast evaluation on the accordingly forecasted state variables and build prediction intervals using the forecasted variances of the state variables. In presence of missing observations, the Kalman filter is carried out by imposing $K_t = 0$ and $v_t = 0$. We perform 83 recursively obtained one-step ahead forecasts, from 2018 to 2100. Figure 4 and 5 show the CO2 atmospheric concentration forecast with respectively the 99% and 50% confidence intervals. Due to the significantly far horizon and the recursively dependent forecasts, the confidence intervals significantly widen, leading to a possible CO2 atmospheric concentration in the year 2100 between 0 and 1200 ppmv in 2100 at the 99% confidence interval. Furthermore, at such confidence interval, all paths are within the possible range. Our forecast lies within RCP4.5 and RCP6, which corresponds to a maximum temperature increase of around 2.75 degrees above pre-industrial level (calibrated temperature from Table 3). Yet, since all possible scenarios are within the confidence range, temperature could potentially increase to a maximum of 4.9 degrees above pre-industrial level or to only a maximum of 1.5 degrees as depicted from the two extreme scenarios. The resulting graphs when $x =$ EU28 and non-OECD are similar and can be found in the Appendix (Figures 28 and 29).

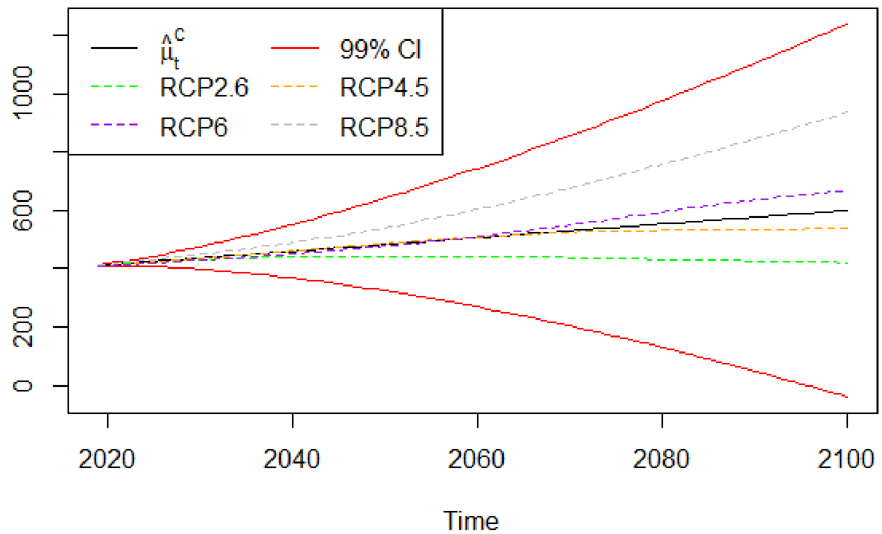

Figure 4: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = US, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

Reducing the confidence interval to 75% then renders unlikely the worst case scenario (RCP8.5) for all x as shown in Figures 30, 31 and 32 in the Appendix. Further decreasing the confidence interval to 50% leads to the additional exclusion of the best case scenario (RCP2.6) when x = US and non-OECD as shown in Figures 5 and 33. On the contrary, we see the striking result, that when we consider x = EU28, we still do include the best case scenario (RCP2.6) in the 50% confidence interval as seen in Figure 6. We see these slight differences due to the fact that we are specifying the state space model in a different way. The underlying principle of both models is the same, but due to these different model specifications we can get different results. All the above results are given the condition that the future will follow the current trend of the growth of CO2 concentrations. Hence, we are quite likely to find ourselves in the medium cases if no changes are imposed on the emission pathway. This shows that in order to reach the goals of the COP21 in Paris, the need for new climate policies becomes urgent.

5.3 Sensitivity Analysis

In this section, we will conduct a sensitivity analysis on the CO2 concentration path for each group of countries. Furthermore, we compare each scenario to the RCP scenarios to evaluate the impact magnitude of different group of countries/individual countries on the temperature rise. We simulate different scenarios in order to do this. In the first setting, we lower the last value of emissions of the group of countries/country by 0.8 GtC/yr, which corresponds to 56% reduction in emissions. In

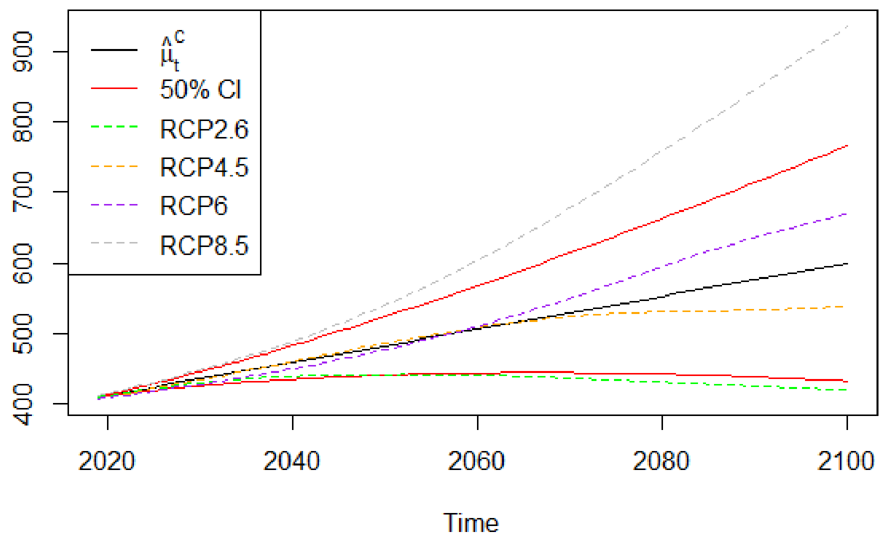

Figure 5: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = US, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

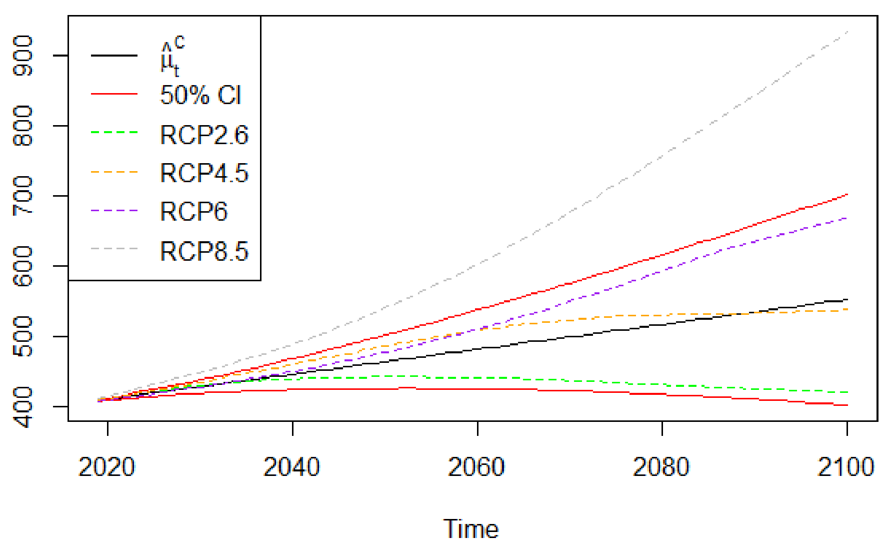

Figure 6: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = EU28, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

the second setting, we increase it by 2 GtC/yr, which corresponds to a 139% increase in emissions in the US. Due to the same magnitude of alteration for each country, we can now evaluate which country has the highest impact and which ones do not have any impact. In this way, we can derive suggestions for policy makers with respect to which countries we should focus on to achieve the goals of a specified maximum temperature increase. Figure 7 and 8 as well as Figure 34- 37 in the Appendix display the future CO2 concentration path for the EU28 countries, so x = EU28. Figure 9 and 10 as well as Figure 38- 41 in the Appendix depict the path for the US (x = US) and Figure 11 and 12 as well as Figure 42- 45 in the Appendix for the non-OECD (x = non-OECD) countries. We recognize that, due to the small sample size and far ahead forecast, the 99% confidence interval is very wide for all groups and, hence, all RCP paths are within possible range. Reducing the confidence interval to 75% already leads to different results. We observe that all groups exclude the worst case scenario. However, whereas for the EU28 countries, the exclusion is very clear and strong, this is not the case for the US and the non-OECD countries, especially with respect to the second simulation where we increase the emissions. In this case, the upper bound of the confidence interval and the worst case scenario almost coincide. Reducing the confidence interval even more to 50%, we can draw several more conclusions. We consider the first simulation, namely a drop by 0.8 GtC/yr, first. Here, we clearly recognize that the confidence interval is tilted towards the best case scenario. The point estimate for year 2100 coincides with the RCP4.5 scenario, meaning a temperature increase of maximum 2.4 degrees. The worst case scenario lies far beyond the upper bound. Moreover, the second worst case scenario is very close to the upper bound. For the non-OECD countries and the US, the best as well as worst case scenarios are excluded from the confidence interval, though the best case scenario is close to the lower bound. Nonetheless, the point estimate for year 2100 is for both groups in between all RCP scenarios and corresponds to a CO2 concentration of approximately 560 ppmv, so a temperature increase of maximum 2.75 degrees. Analyzing the second simulation scenario, we observe that all groups exclude the worst and best case scenario from the interval. The worst case scenario still lies quite far outside of the interval whereas the best scenario is relatively close to the lower bound. Overall, we see that the decrease of emissions in the EU28 countries has the biggest impact on the forecasted CO2 concentration pathway. The confidence intervals are tilted towards the best case scenario and the point estimate is very close to the RCP4.5, so a maximum temperature increase of 2.4 degrees. Moreover, the worst case scenario lies far away from the upper bound of the confidence interval. The US and non-OECD countries experience similar consequences after a decrease/increase in emissions. Both groups show that an alteration of the emissions have less impact on the forecasted CO2 concentration path in comparison to the EU countries. Moreover, from the second simulated scenario, we see that an increase in the emissions of the EU countries has less negative impact than of the other two groups. For these, the upper bound of the 75% confidence interval almost coincides with the worst case scenario, so it is almost included, while this is clearly not the case for the EU countries. Hence, although the EU countries have a higher positive impact when reduction is imposed, the US and non-OECD countries have a bigger negative impact when an increase in emission takes place. This is important to keep in mind when introducing new regulations. Even though the impact of developing countries on global CO2 concentration may not significantly differ from the one of developed countries, their economic activity might be harmed by policies which aim at reducing CO2 emissions. Therefore, developed countries are urged to lean towards these policies.

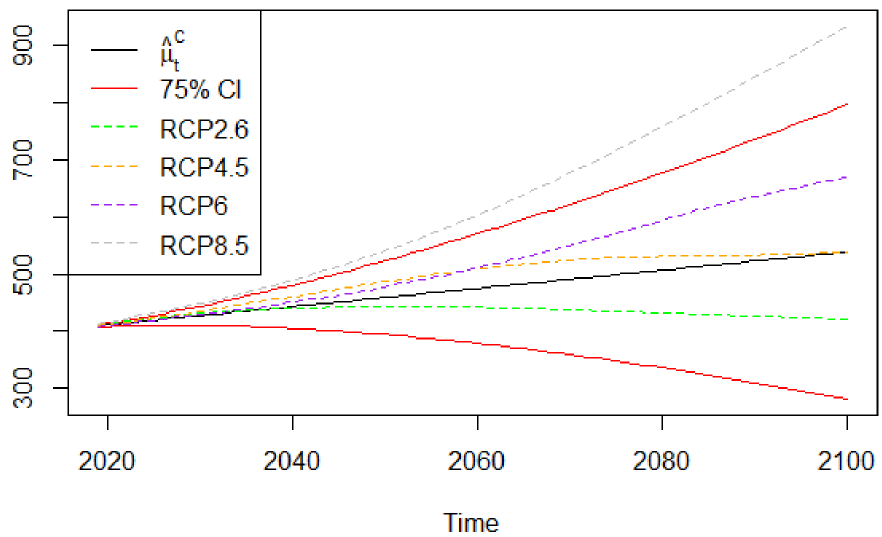

Figure 7: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of EU dropped by 0.8 GtC/yr, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

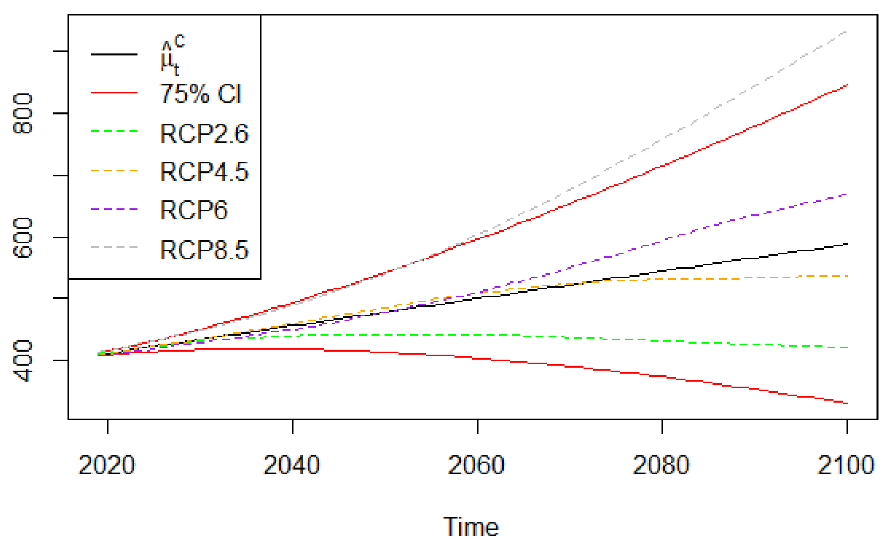

Figure 8: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of EU increased by 2 GtC/yr, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

5.4 CO2 emissions and economic activity

As mentioned by Andersson and Karpestam (2013), while there is strong consensus in scientific communities that rising global temperatures must be combated, there is also a concern that imple-

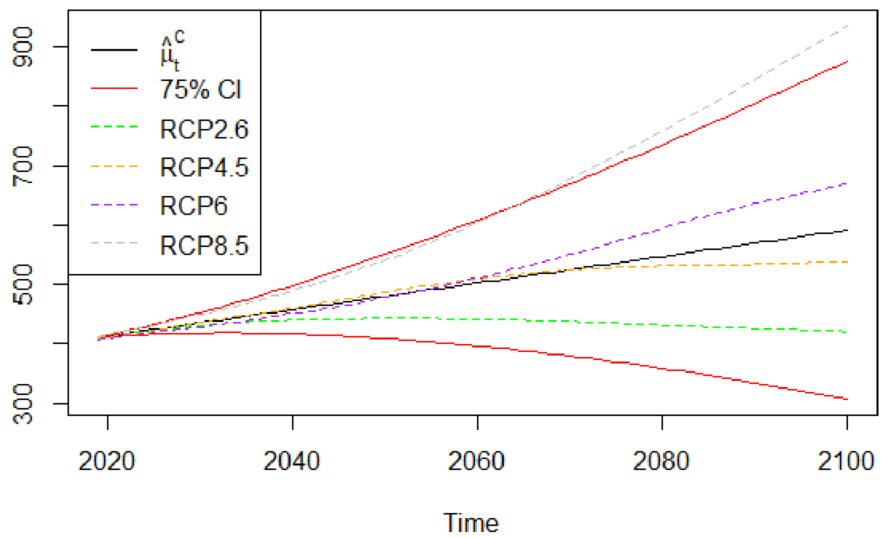

Figure 9: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of US dropped by 0.8 GtC/yr, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

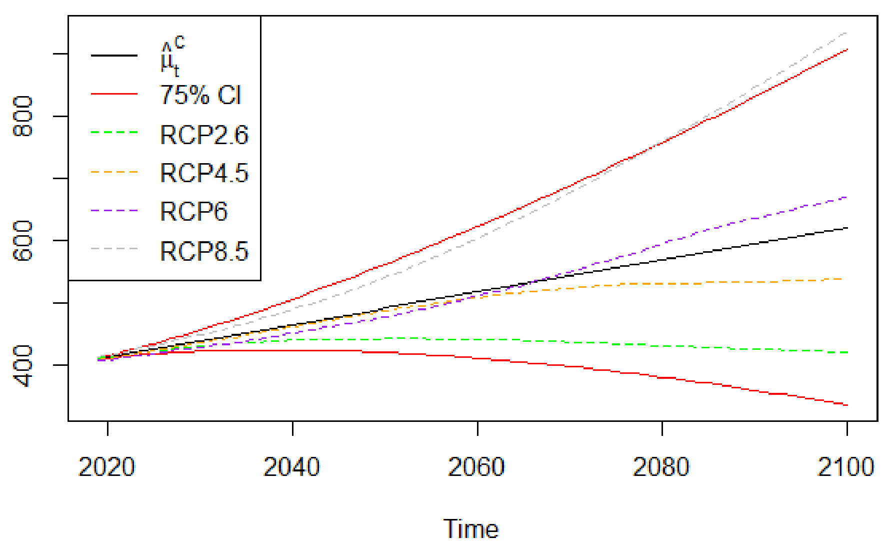

Figure 10: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of US increased by 2 GtC/yr, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

menting emissions reductions too quickly will limit economic growth. In this section we focus on the US emissions. We extend our initial model with the addition of its industrial production index

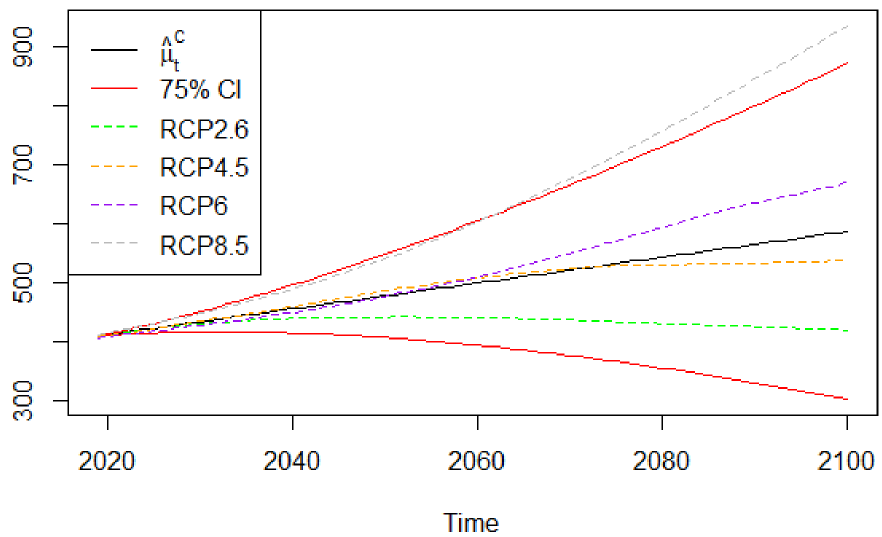

Figure 11: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of Non-OECD dropped by 0.8 GtC/yr, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

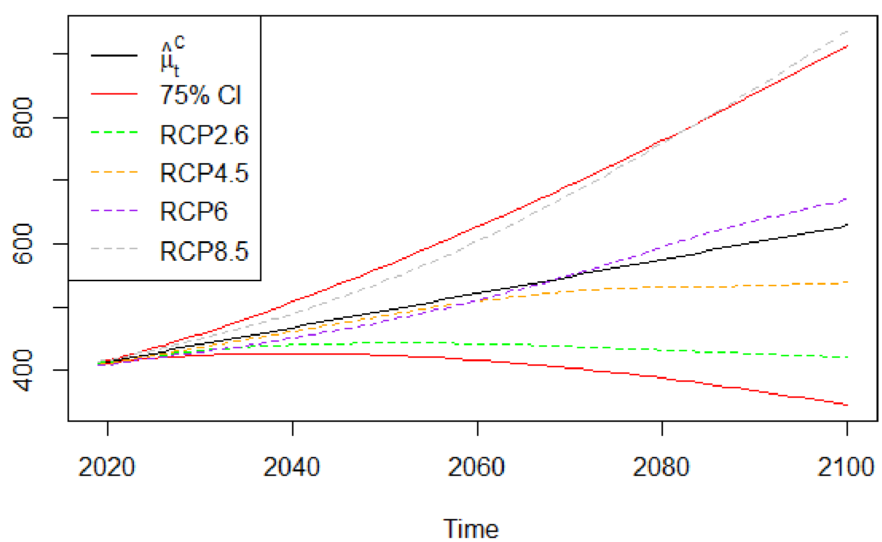

Figure 12: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of Non-OECD increased by 2 GtC/yr, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

as an indicator of US economic activity, denoted I_t,

$$\begin{bmatrix} C_t \\ G_t \\ E_t^R + E_t^x - S_t \\ E_t^R \\ S_t \\ E_t^x \\ I_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 1 & 0 \\ 0 & 1 & -1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_t^C \\ \mu_t^R \\ \mu_t^S \\ \mu_t^x \\ \mu_t^I \end{bmatrix} + \epsilon_t, \tag{7}$$

where ϵ_t is a vector stacking the seven error terms of the observation equations, they are assumed independently normally distributed with mean zero and distinct variance: $\epsilon_t \sim N(0, H)$, $H = \text{diag}(\sigma^2_{C,\epsilon}, \sigma^2_{G,\epsilon}, \sigma^2_{R+x-S,\epsilon}, \sigma^2_{R,\epsilon}, \sigma^2_{S,\epsilon}, \sigma^2_{x,\epsilon}, \sigma^2_{I,\epsilon})$. The transition equations are then as follows,

$$\begin{bmatrix} \mu_t^C \\ \mu_t^R \\ \mu_t^S \\ \mu_t^x \\ \mu_t^I \end{bmatrix} = \begin{bmatrix} 1 & 1 & -1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1}^C \\ \mu_{t-1}^R \\ \mu_{t-1}^S \\ \mu_{t-1}^x \\ \mu_{t-1}^I \end{bmatrix} + \eta_t. \tag{8}$$

What changes in this model is that we assume that the error terms of the state variables of μ_t^x and μ_t^I are correlated. Hence, $\eta_t \sim N(0, Q)$, where

$$Q = \begin{bmatrix} \sigma^2_{C,\eta} & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{R,\eta} & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{S,\eta} & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{x,\eta} & \rho\sigma_{I,\eta}\sigma_{x,\eta} \\ 0 & 0 & 0 & \rho\sigma_{I,\eta}\sigma_{x,\eta} & \sigma^2_{I,\eta} \end{bmatrix}.$$

As such, it implies that the conditional expectation of US emissions will depend on its own past value but also on the contemporary change of the economic activity,

$$\mathbb{E}[\mu_{t+1}^x | \mu_t^x, \mu_{t+1}^I] = \mu_t^x + \rho \frac{\sigma_{x,\eta}}{\sigma_{I,\eta}} (\mu_{t+1}^I - \mu_t^I). \tag{9}$$

Intuitively, an increase in production, given a state of technology and other factors, should increase emissions.

In Section 5.3, we investigated the effect of a change in emissions on CO2 concentrations. We hence just fix future emission paths and performed forecasts of levels of concentrations. We now investigate the means for such reduction in CO2 emissions. As just mentioned we assume that emissions are driven by changes in production, we hence investigate the sensitivity of US CO2 emissions to variations in production.

The hyperparameters of the model are estimated in the same way as in Section 4, yielding an estimated correlation of $\hat{\rho} = 0.59$. We then perform similar sensitivity analyses by imposing future paths of economic activity. We consider two scenarios. The first one corresponds to a permanent decrease of 20% in production and the forecast of US CO2 emissions is depicted in Figure 13. As expected from the conditional expectation depicted in Equation (9), the forecast of emissions falls by roughly 62% as the production drops by 20% and then is remains constant. The 62% decrease in US emissions is roughly equal to the decrease of 0.8 GtC simulated in Section 5.3. This signals that CO2 emissions responds with a magnitude 3 times higher than the shock in production. Yet, such a cut in production is rather drastic. Instead, we consider a second scenario in which production gradually decrease by 2.5% a year, corresponding to the same decrease in emissions by 2100. Figure 14 shows the forecast over the next 83 years of US CO2 emissions with such scenario. The scenario, more realistic, indicates that by gradually decreasing production by 2.5% a year, emissions will already be reduced by a half in 2040.

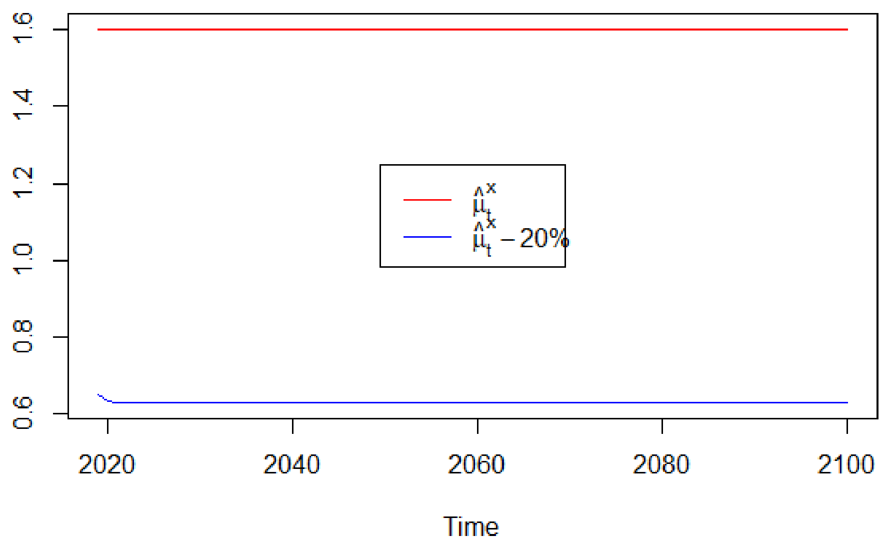

Figure 13: Out of sample forecasts of μ_t^X of E_t^x in GtC/y, when $x = $ US, assuming a permanent decrease of 20% in production for the out-of sample period.

The results in this section suggests that emissions reduction, at least in the US, do not require such significant decrease in production, as feared. Emissions in the US could, as this model indicates, be reduced by half by 2040 if production was gradually decreased by 2.5% a year. Of course, this section assumes all other factors constant, as well as no technological progress. Technological progress and the expansion of renewable energy allows production to increase while having decreasing emissions. On the other hand, territorial emissions could be reduced while keeping production constant if offshoring is performed in developing countries where climate regulations are more lenient. Via such process, territorial emissions indeed decrease but global emissions remain unchanged.

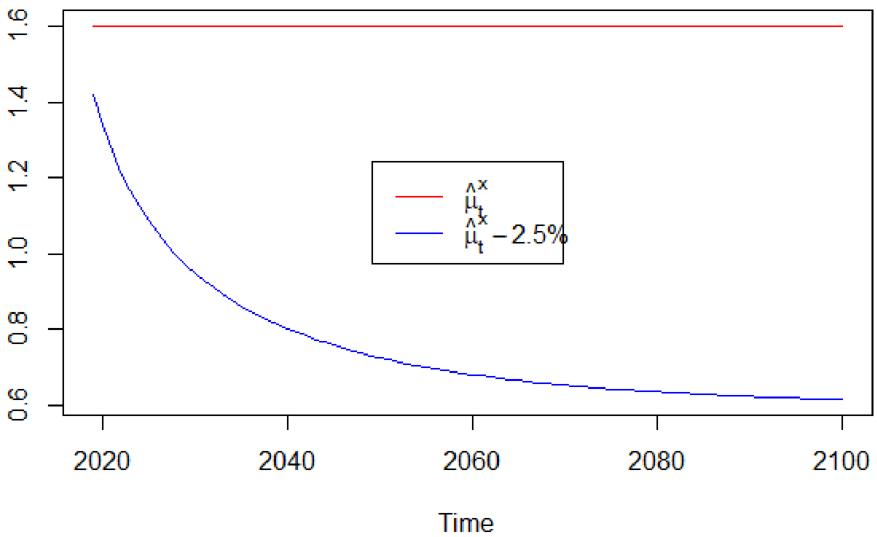

Figure 14: Out of sample forecasts of μ_t^X of E_t^x in GtC/y, when $x =$ US, assuming a decrease of 2.5% per year in production.

6 Discussion

A key motivation to undertake this study has been to model CO2 atmospheric concentration using an econometric approach. The basis of our model is the Global Carbon Budget Equation and by using a state-space approach we intend to tackle the measurement errors that climate data are subject to. Following the critiques of Friedlingstein (2015) and Bennedsen et al. (nd), we do recognize that a drawback of the constructed model is that it does not incorporate the carbon-climate feedback. Since the discussion of these effects are still heated, we do realize that it is worth while to expand the model and include these effects. Therefore, we suggest this for further research, following the idea of coupled carbon-climate models.

Moreover, due to having only yearly data at hand, the sample size is relatively small (59 data points). Hence, drawing reliable conclusions is very hard and limited, e.g. tests like the ADF-test may not be valid. We also acknowledge this problem in the forecasts. Predicting more than 80 out-of-sample forecasts with a model that is estimated using less than 60 observations leads to substantial uncertainty, especially the further in the future the forecasts are.

A third limitation is the number of variables used in the model. We decided to merge the rest of the world's emissions with the global land-use change emissions and also merged the two sink variables to reduce the dimensionality. In this way, we cannot distinguish the emissions and sinks and cannot draw individual conclusions. Additionally, we limited our data set to those 6 or 7 variables while potentially other external factors could influence CO2 concentration, such as the direct, or indirect effects of other greenhouse gas, population growth or technological progress for instance. Furthermore, while looking at the effects of changes in production on the US CO2 emissions, even more external factors may be affecting the link between the two variables, such as offshoring factories as explained in the previous part.

Another major shortcoming arises in the model specification for the impact of different regions. Here, we evaluate individual models for each region instead of modelling them together. This is mainly due to the small sample size. We cannot estimate all these parameters given the few data points. In this way, we can only check which group of countries have a higher impact on the evolution of the CO2 concentration path, but we cannot investigate the different future paths if we alter each of the regions differently, e.g. in a first scenario reduce emissions significantly in the US and only slightly in the EU28 countries and in a second scenario vice versa.

Another limitation arises in the sensitivity analysis, where we set the value of emissions equal to the last value plus or minus a specific amount and then keep it constant in the model. This is done in order to then evaluate the path of the carbon concentration after a policy intervention for example. However, this is not realistic due to two reasons. First of all, it is assumed that the value of emissions will stay constant over time. This is highly unlikely. Second, the model currently assumes a big jump in the value of emissions at the beginning to investigate the different scenarios. An extension of this simulation study would be to let the values gradually increase/decrease at a specific rate over time, hence find a decreasing time series of emissions such that the value of C_{2100} is equal to the desired value depending on which scenario we are investigating.

To put it in a nutshell, the model constructed in this paper is rather simplified and may lack dynamics or external factors. However, it tackles the problem of measurement errors, it is based on the Carbon Budget Equation, and its forecasts in are line with climate specialists scenarios forecasts. We investigate individual effects of changes in three regions' CO2 emissions and the effect of a drop in production on CO2 emissions in the US. Yet, further research could extend the constructed state space model to incorporate the effect of countries combined.

7 Conclusion

Climate change is nowadays a key topic of interest in political discussions. It is crucial to have proper models and perform accurate forecasts of climate-related variables to efficiently tackle the issues that climate change brings. In order to introduce new policies, it is important not only to clearly identify the impact of separate groups of countries but also to evaluate the consequences of such policies on economic activity for instance. This gave rise to multidisciplinary approaches, such as the use of econometric methods to model climate series and their dynamics. This paper focuses on measuring the impact of changes in CO2 emissions in different regions of the world on the atmospheric concentration and then investigates by what means such reductions can be achieved with the example of the US.

We propose a state space approach that takes into account the measurement errors to which climate data are subject. This was motivated by the persistent Global Carbon Budget Equation imbalance observed in practice over the past years. The model is based on this equation and allows to jointly estimate and forecast all the unobserved components driving the observed variables of the Budget Equation and CO2 concentrations. Our analysis provides insights into a distribution scheme for the emission reductions across groups of countries in order to reach goals set during climate summits, such as the maximum of 2 degrees rise above pre-industrial levels set by the COP21, and further explores the consequences of these schemes on economic activity.

We compare our forecast of CO2 concentration from 2018 to 2100 to Representative Concentration Pathways that correspond to distinct scenarios leading to different temperature increases above pre-industrial levels. We find that if all variables follow the current trend, any scenario from a maximum increase of 1.5 degrees above pre-industrial level to a maximum increase of 4.9 degrees lies within the 99% confidence interval for all three regions considered. Even though the worst case scenario is excluded in all of the 50% confidence intervals, so is the best case scenario in most of the models, which corresponds to a maximum increase of 1.5 degrees.

We perform a sensitivity analysis by imposing future emission paths of specific countries and investigate their effect on potential future temperature rise under RCP scenarios. Further, we compare the magnitude of the impact among three regions, the US, the EU28 and the non-OECD countries. We find that if emissions of one group of countries are altered and all other variables follow current trends, any scenario from a maximum increase of 1.5 degrees above pre-industrial level to a maximum increase of 4.9 degrees lies within the 99% confidence interval. Further, reducing the confidence intervals to 75% and 50%, we can conclude that the confidence intervals for the EU28 countries is tilted towards the best case scenario in a reduction of emissions and the worst case scenario lies far outside of the interval. For the US and non-OECD countries, on the contrary, we find that the best case scenario is sometimes even excluded from the confidence interval. Overall, we do see a little shift towards the best case scenario for each region. Hence, combined this can lead to an achievement of the goals set. While we do not find significant difference in the effects of changes in CO2 emissions between developed and developing countries, the fact is developing countries activity may be severely harmed by policies intending to reduce emissions. Hence, even though their impact on global CO2 concentration may be the same, they cannot be asked to have policies of the same magnitude as developed countries.

We then investigate how a decrease in CO2 emissions could actually be achieved in the case for the US. We assumed that CO2 emissions are affected by changes in production. We find that in the US, CO2 emissions react to changes in production with a magnitude 3 times higher than the actual change in the production. While people fear that decreasing emissions may significantly harm economic activity, our model indicates that by gradually decreasing production by 2.5% a year, CO2 emissions could be reduced by a half by 2040. We did not take into account various external factors that may affect the relationship between the two variables, and leave that for further research.

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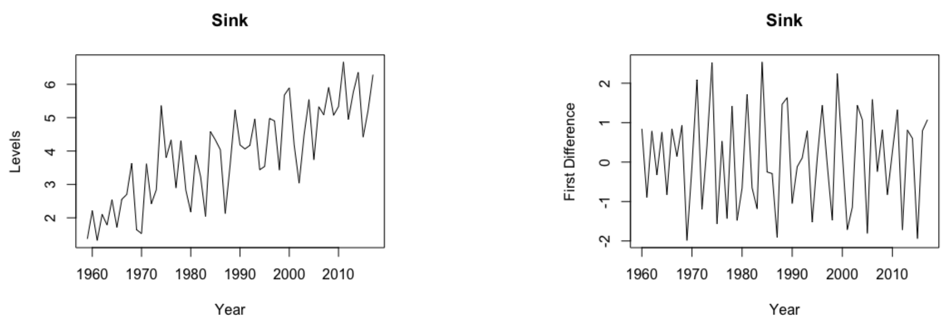
Appendices

	Atmospheric Growth	Emission without US	Emission without EU	Emission without Non-OECD	Sink
Mean	3.258692	5.957751	6.193513	4.509751	3.88693
Standard Deviation	1.381219	1.92756	2.101062	0.6317307	1.41866

Table 4: Summary Statistics

	Emission US	Emission EU	Emission Non-OECD	Production Index
Mean	1.323834	1.088072	2.771834	65.62633
Standard Deviation	0.2534717	0.1417442	1.544902	26.58313

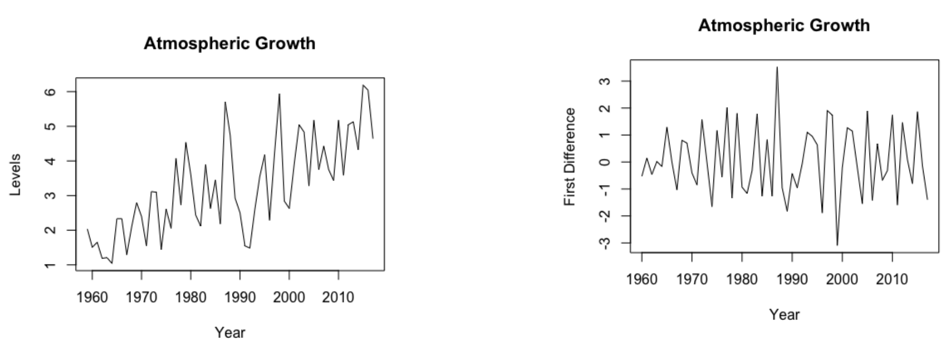
Table 5: Summary Statistics



(a) Sink Level

(b) Sink First Difference

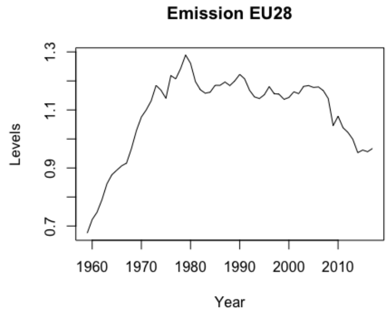
Figure 15: Sink



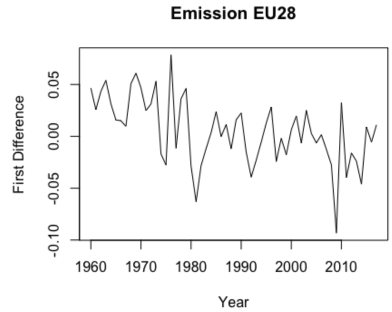
(a) Atmospheric Growth Level

(b) Atmospheric Growth First Difference

Figure 16: Atmospheric Growth

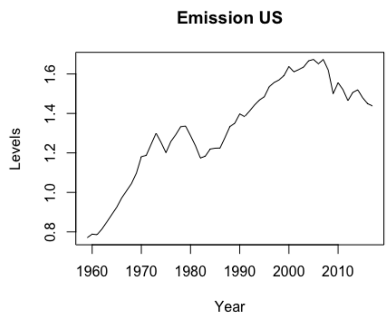


(a) Emission EU28 Level

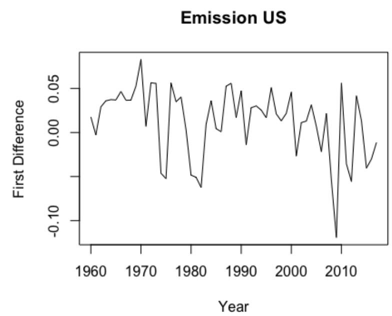


(b) Emission EU28 First Difference

Figure 17: Emission EU28

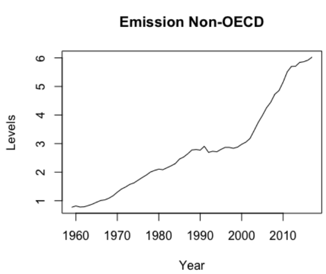


(a) Emission US Level

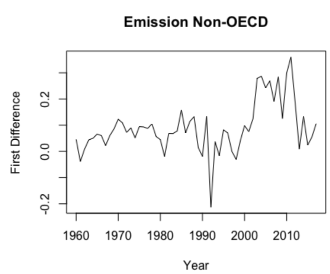


(b) Emission US First Difference

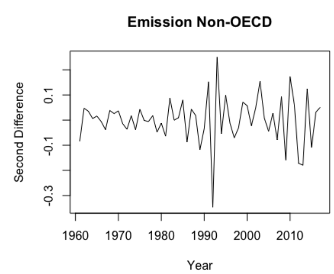
Figure 18: Emission US



(a) Emission Non-OECD Level

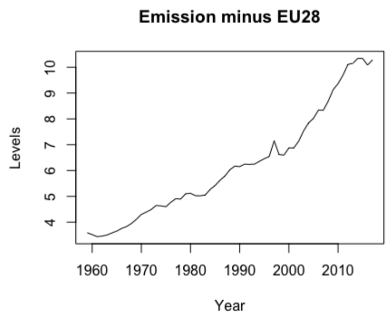


(b) Emission Non-OECD First Difference

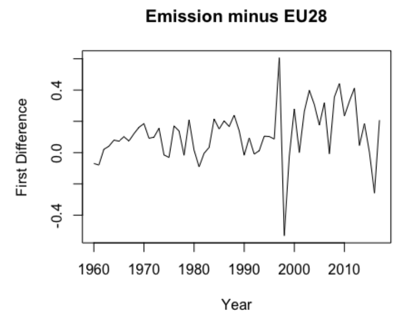


(c) Emission Non-OECD Second Difference

Figure 19: Emission Non-OECD

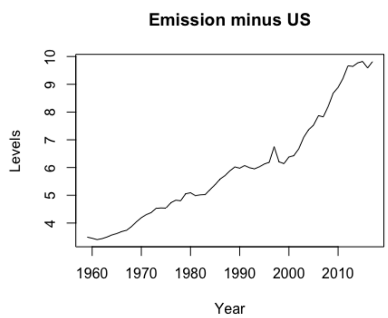


(a) Emission without EU28 Level

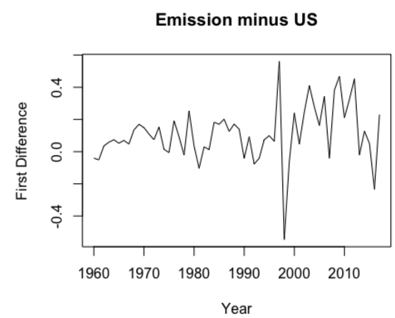


(b) Emission without EU28 First Difference

Figure 20: Emission without EU28

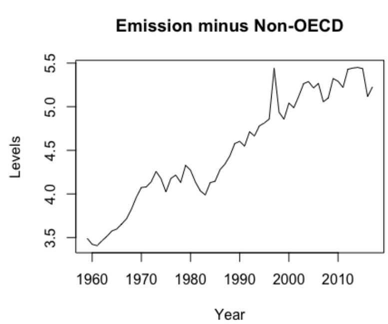


(a) Emission without US Level

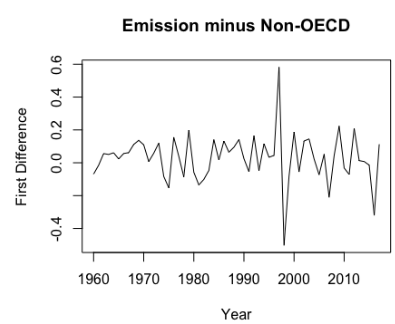


(b) Emission without US First Difference

Figure 21: Emission without US

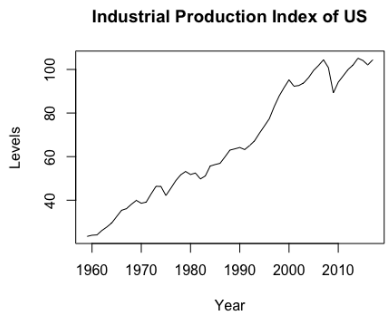


(a) Emission without Non-OECD Level

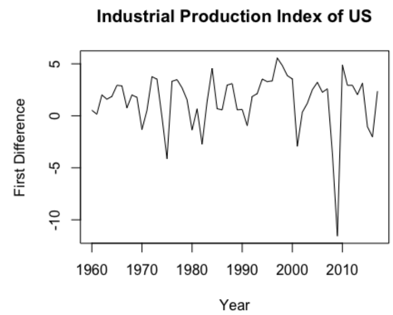


(b) Emission without Non-OECD First Difference

Figure 22: Emission without Non-OECD



(a) Production Index Level



(b) Production Index First Difference

Figure 23: Industrial Production Index US

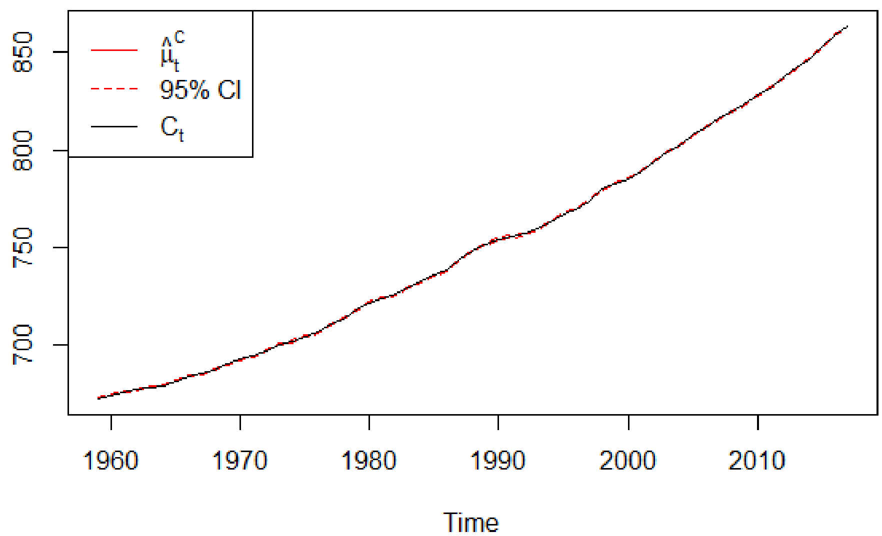


Figure 24: In-sample estimates of the state variable μ_t^C of C_t in GtC/yr, when x = EU28, together with their 95% confidence intervals.

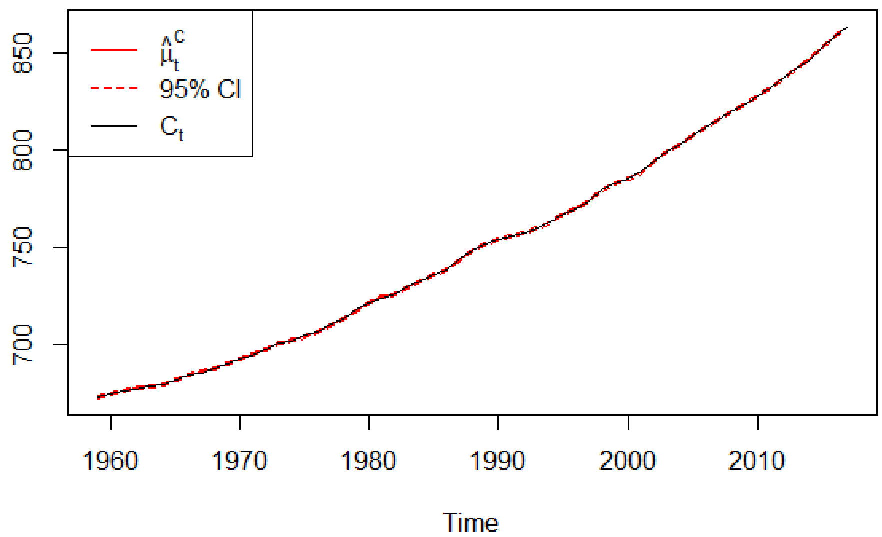


Figure 25: In-sample estimates of the state variable μ_t^C of C_t in GtC/yr, when x = non-OECD, together with their 95% confidence intervals.

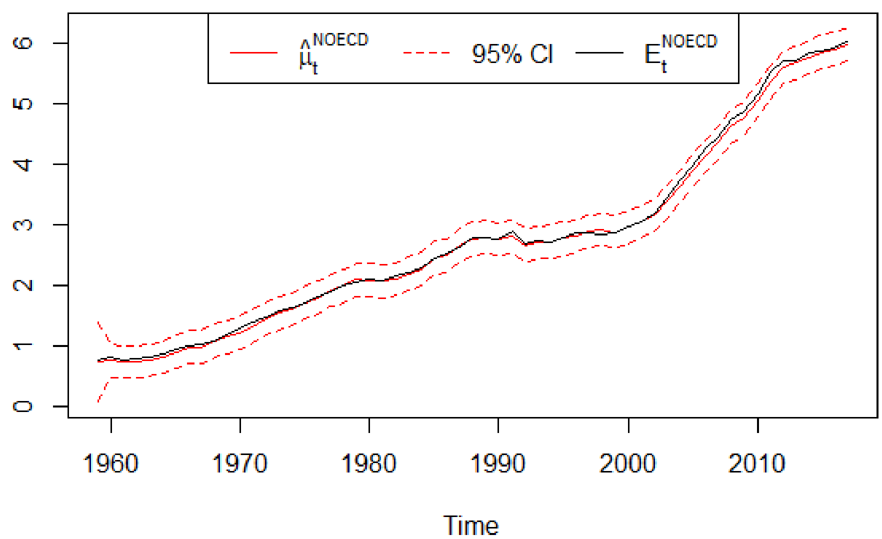


Figure 26: In-sample estimates of the state variable μ_t^x of E_t^x in GtC/yr, when x = non-OECD, together with their 95% confidence intervals.

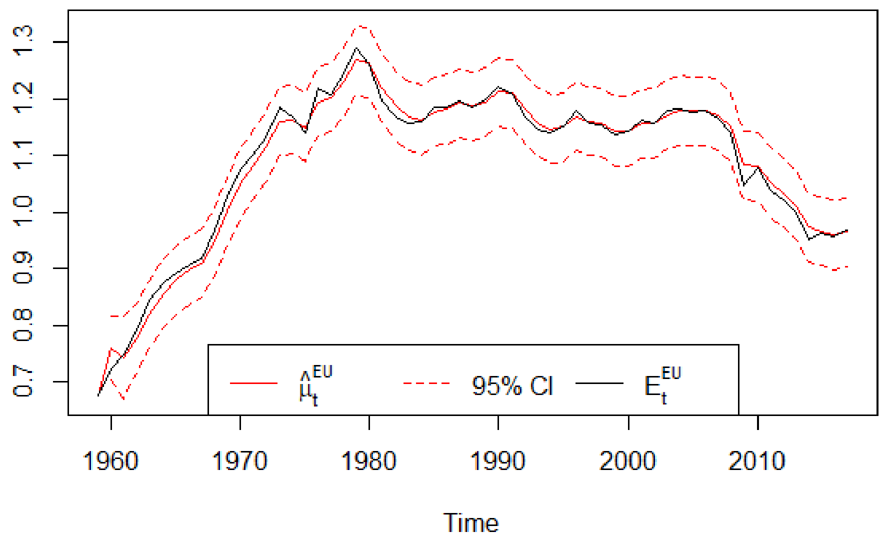


Figure 27: In-sample estimates of the state variable μ_t^x of E_t^x, when x = EU28 in GtC/yr, together with their 95% confidence intervals.

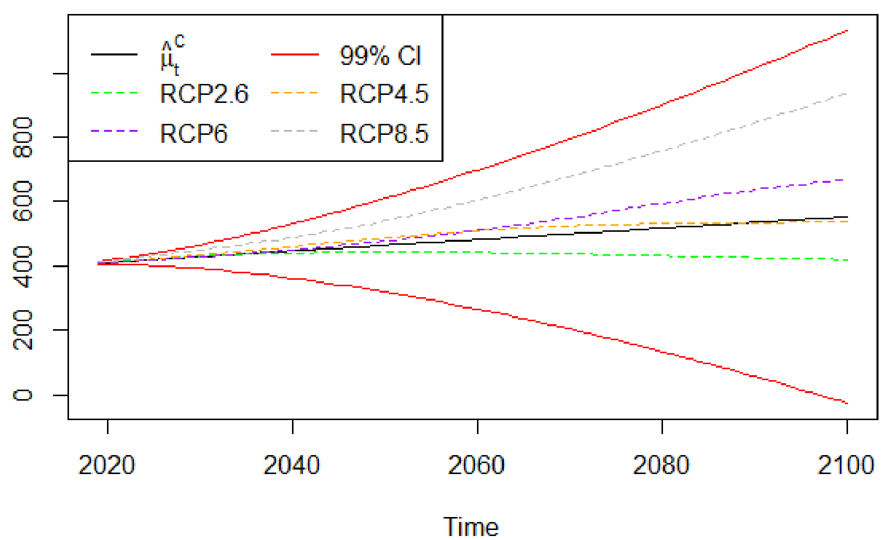


Figure 28: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = EU28, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

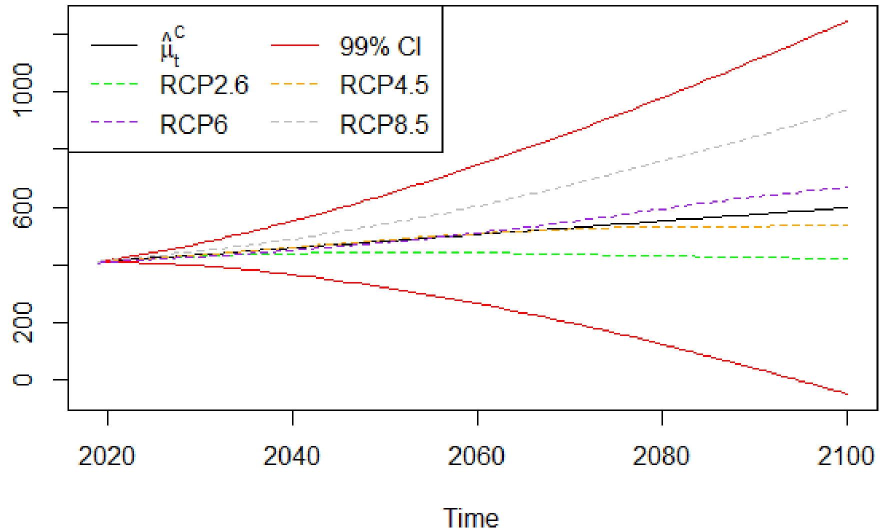


Figure 29: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = non-OECD, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

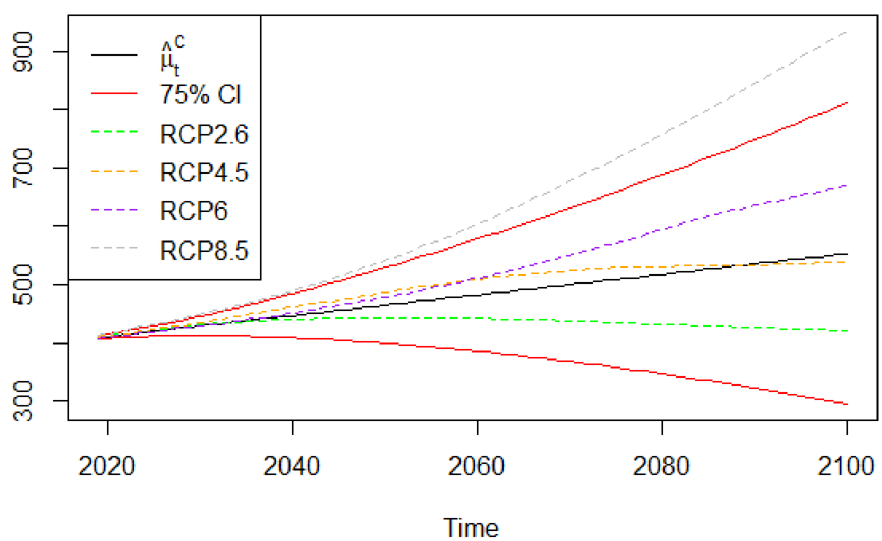


Figure 30: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = EU28, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

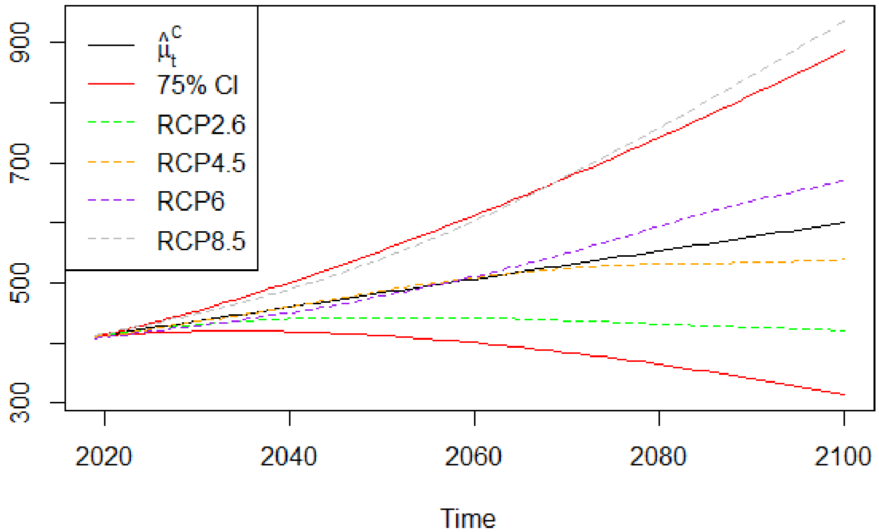


Figure 31: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = US, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

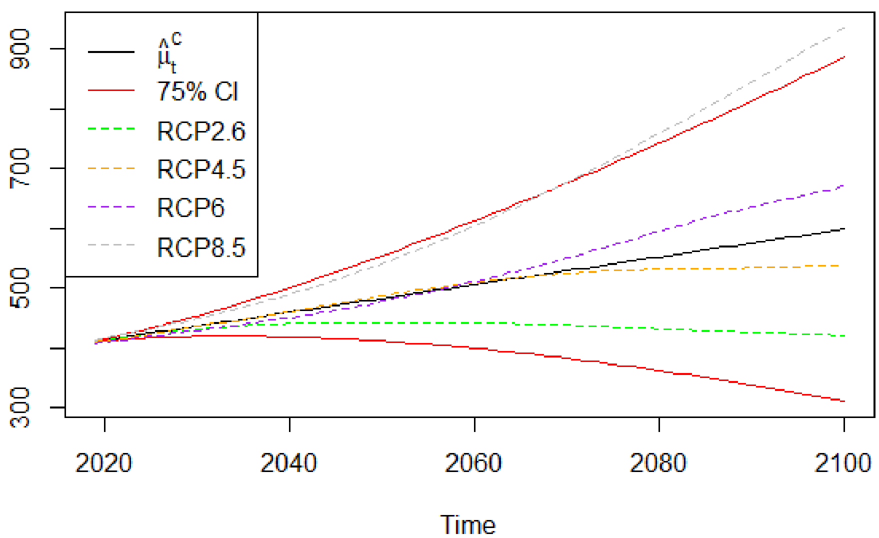


Figure 32: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = non-OECD, together with their 75% confidence intervals, compared to the RCP forecasted scenarios.

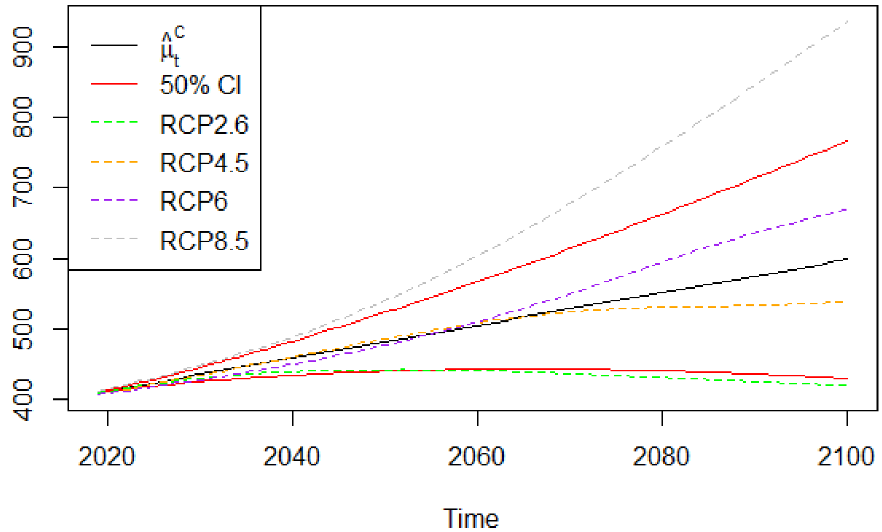


Figure 33: Out of sample forecasts of μ_t^C of C_t in ppmv, when x = non-OECD, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

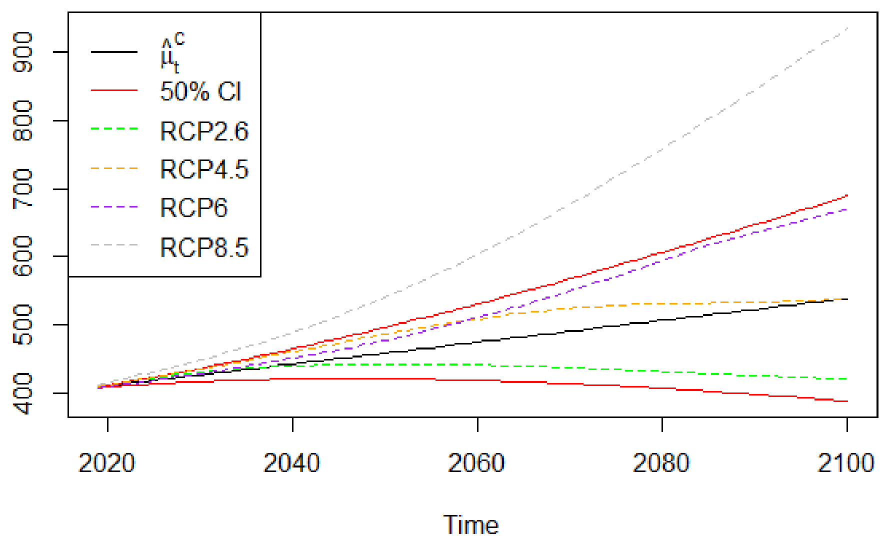


Figure 34: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of EU28 dropped by 0.8 GtC/y, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

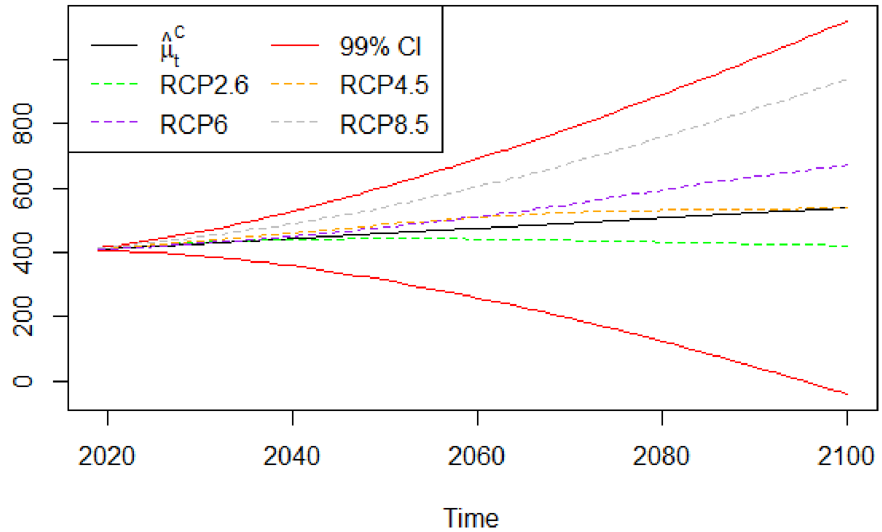


Figure 35: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of EU28 dropped by 0.8 GtC/y, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

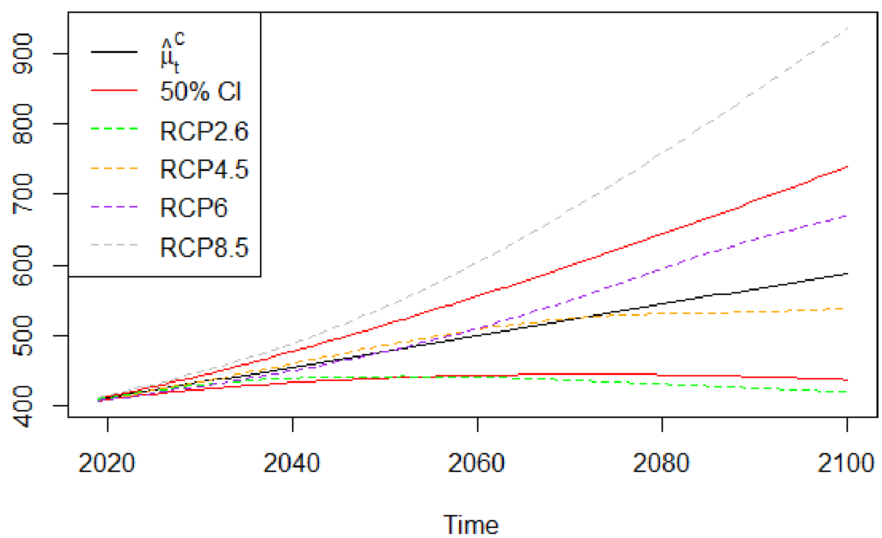


Figure 36: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of EU28 increased by 2 GtC/y, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

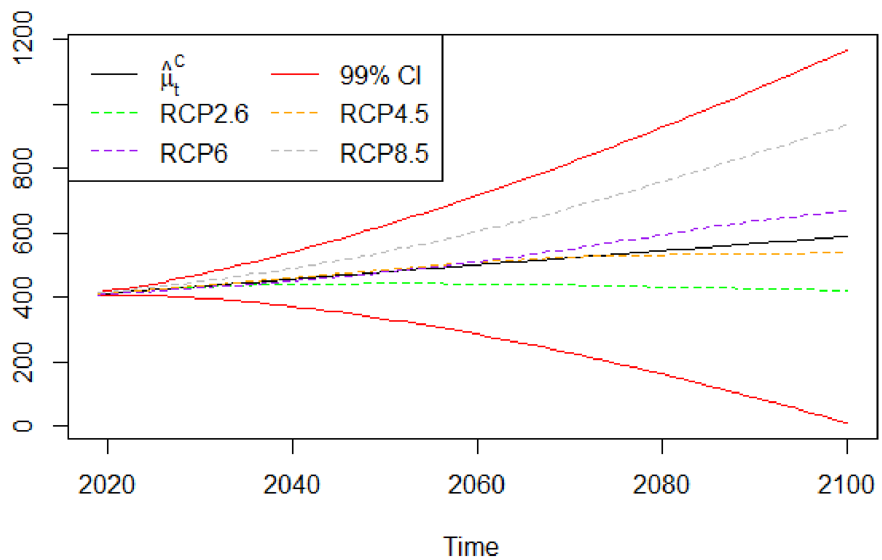


Figure 37: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of EU28 increased by 2 GtC/y, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

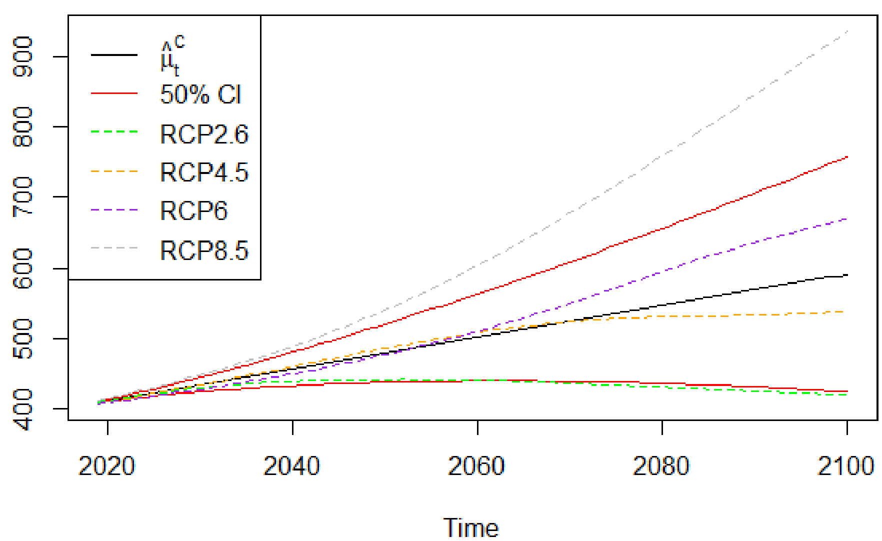


Figure 38: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of US dropped by 0.8 GtC/y, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

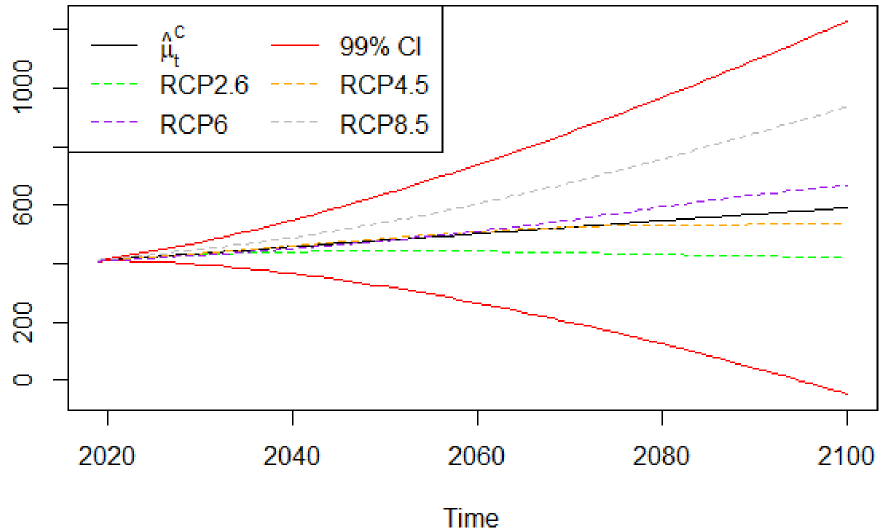


Figure 39: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of US dropped by 0.8 GtC/y, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

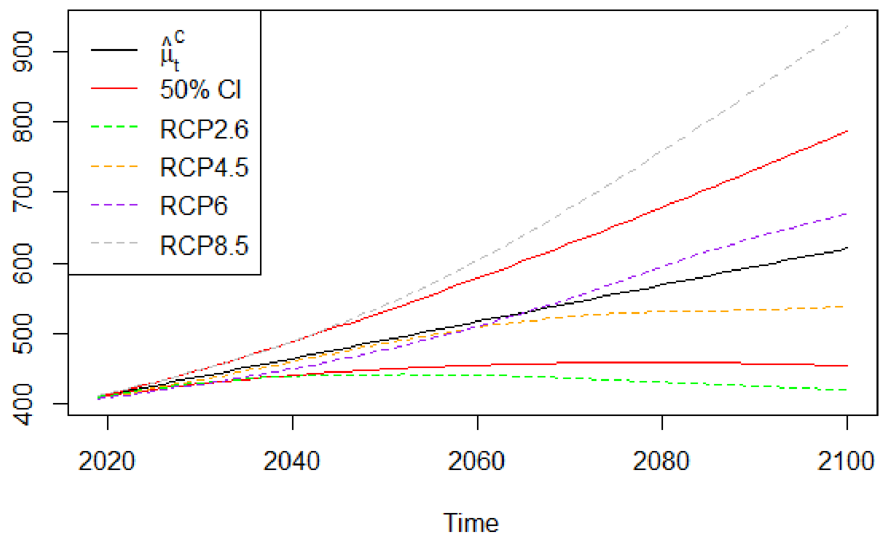


Figure 40: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of US increased by 2 GtC/y, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

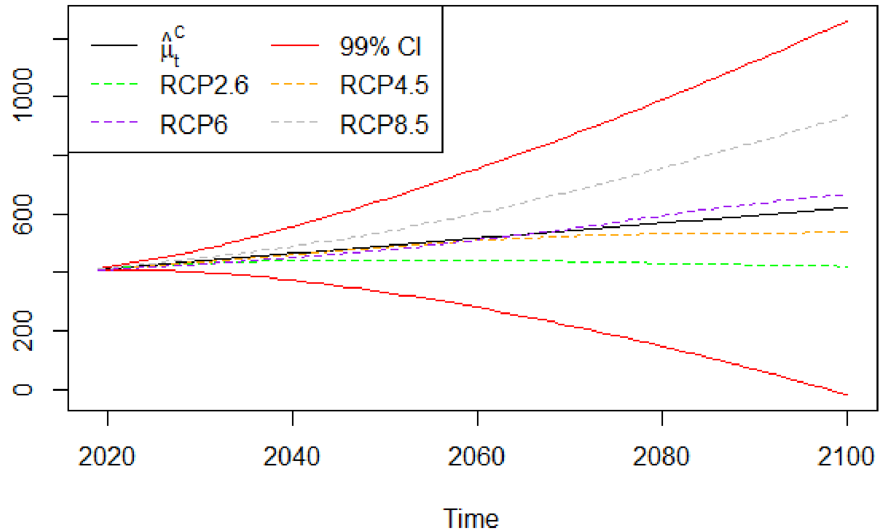


Figure 41: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of US increased by 2 GtC/y, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

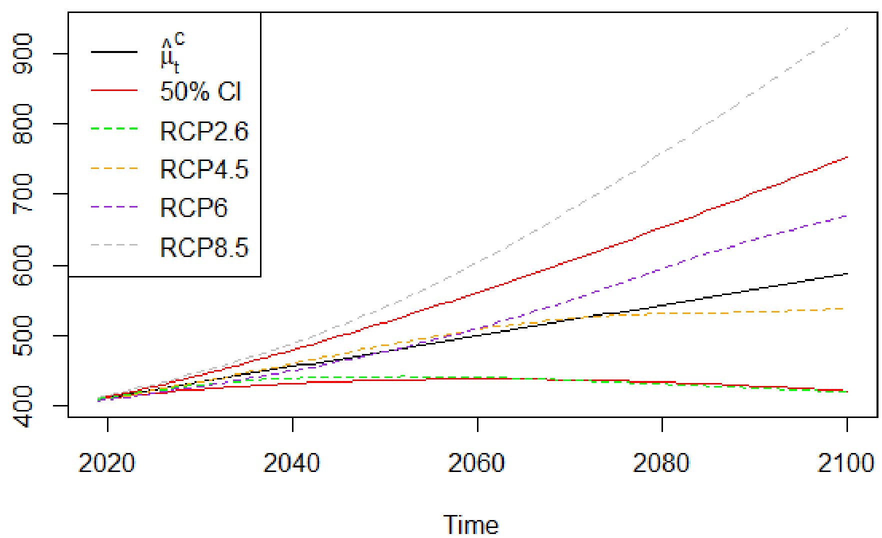


Figure 42: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of Non-OECD dropped by 0.8 GtC/y, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

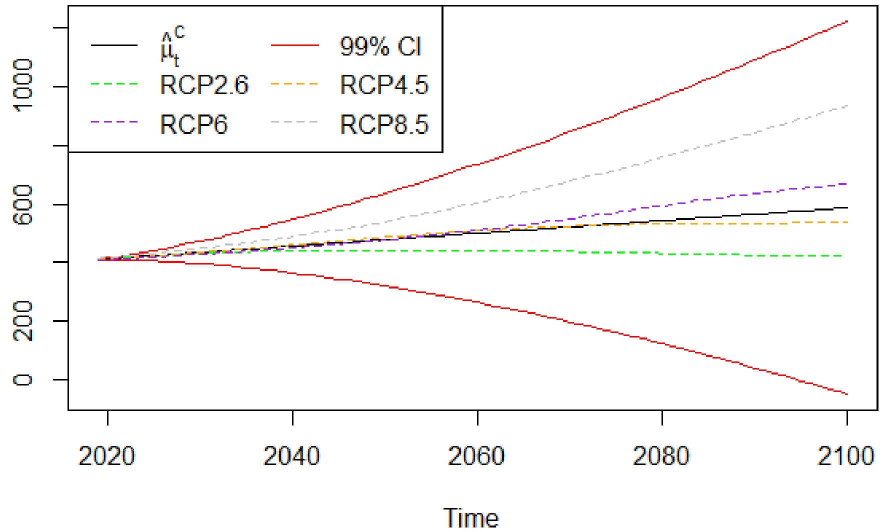


Figure 43: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of Non-OECD dropped by 0.8 GtC/y, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.

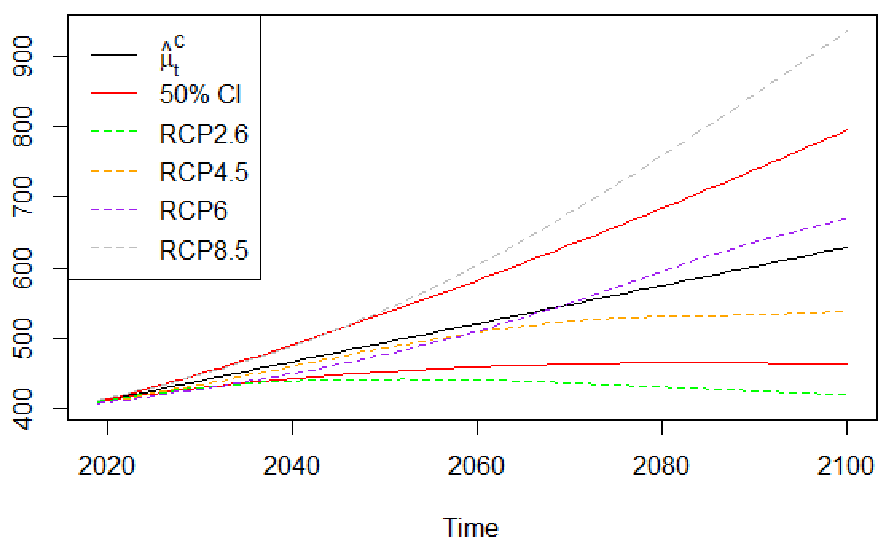


Figure 44: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of Non-OECD increased by 2 GtC/y, together with their 50% confidence intervals, compared to the RCP forecasted scenarios.

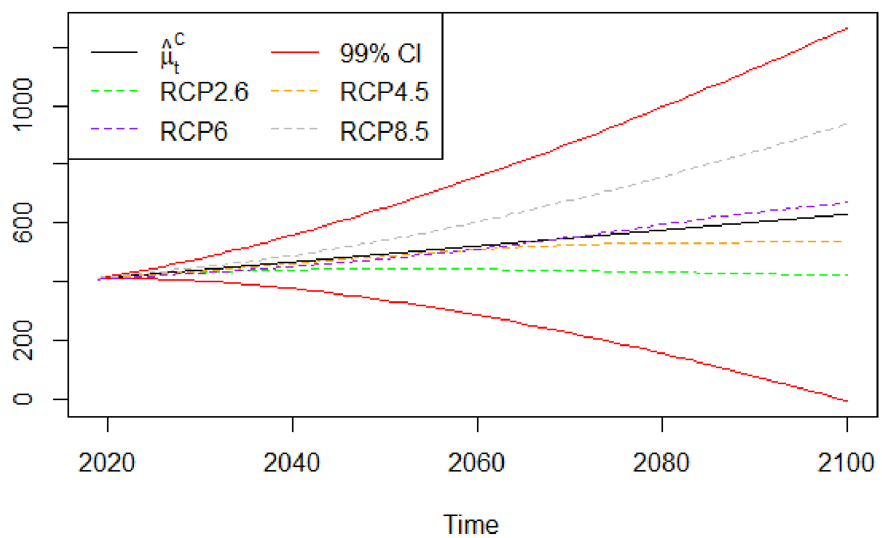


Figure 45: Out of sample forecasts of μ_t^C of C_t in ppmv if emissions of Non-OECD increased by 2 GtC/y, together with their 99% confidence intervals, compared to the RCP forecasted scenarios.