World GDP, Anthropogenic Emissions, and Global Temperatures, Sea Level, and Ice Cover*

Luca Benati
University of Bern†

Abstract

I use Bayesian structural VARs with stochastic volatility to study the dynamics of global land and ocean temperatures, the sea level, and ice cover in the Northern emisphere since 1850, by exploiting (i) their long-run equilibrium relationship with climate change drivers (CCDs) and (ii) the relationship between world GDP and anthropogenic CCDs. Random variation in CCDs that causes a permanent increase in land temperatures by 1 Celsius degree is associated with a 16% permanent decrease in world GDP, with 94% of the posterior distribution below zero. Assuming that trend GDP growth will remain unchanged after 2024, and the world economy will fully decarbonize by 2050, land temperatures and the sea level are projected to increase by 4.9 degrees and 45 centimeters respectively compared to pre-industrial times. Further, uncertainty is substantial, pointing to significant upward risks. Because of this, bringing climate change under control will require a massive programme of carbon removal from the atmosphere, in order to bring anthropogenic CCDs back to the levels of the 1970s.

Keywords: Climate change; Bayesian VARs; stochastic volatility; cointegration; forecasting; conditional forecasts; structural VARs.
JEL Classification: E2, E3.

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Department of Economics, University of Bern, Schanzeneckstrasse 1, CH-3001, Bern, Switzerland. Email: luca.benati@vwi.unibe.ch

1 Introduction

For more than a decade global temperatures have been consistently breaking records nearly every year. Against this background, the scorching summers of 2022, 2023 and 2024, characterized by heatwaves, droughts, wildfires and floods of an unprecedented spread and intensity, have highligthed in the starkest possible way the severity of the threat posed by climate change.

In this paper I use Bayesian structural VARs with stochastic volatility in order to study the dynamics of global land and ocean temperatures, the sea level, and ice cover in the Northern emisphere since 1850, by exploiting

(*i*) the relationship between world GDP and anthropogenic drivers of climate change (CO2, methane, clorofluorocarbons, sulphur emissions, ...);

(*ii*) the long-run equilibrium relationship between global temperatures and either the sea level or ice cover; and

(*iii*) the long-run equilibrium relationship between temperatures and all climate change drivers (CCDs) jointly considered, both anthropogenic and non-anthropogenic (i.e., volcanic activity and solar irradiance). Such long-run relationship is a key tenet of climate science, and it is in fact an implication of physics laws that can be (and it has been) tested within a laboratory setting under controlled conditions.

In line with the climate science literature, the literature on the econometrics of climate change, and the Intergovernmental Panel on Climate Change (IPCC) reports, I summarize the *joint* impact on temperatures of *all* CCDs via a single index, their so-called Joint Radiative Forcing (JRF). Intuitively, the radiative forcing of individual CCDs provides a quantitative measure, based on formulas from physics, of their ability to *trap heat* in the atmosphere. The JRF index provides therefore a quantitative summary of the *overall* ability of all CCDs *jointly considered* to trap heat. Because of this the JRF index is, in fact, *all that matters* as far as climate change is concerned. Permanent increases (decreases) in the JRF cause subsequent corresponding increases (decreases) in global temperatures.

I estimate VARs for world GDP, global temperatures, the sea level, ice cover in the Northern emisphere, anthropogenic radiative forcing (RF), and the radiative forcings of volcanic activity and solar irradiance. I impose

(1) *exogeneity* of both volcanic activity and solar irradiance with respect to the rest of the system;

(2) in line with a vast literature, *cointegration* between the JRF index and global temperatures;

(3) *cointegration* between global temperatures and either the sea level or ice cover, a feature of the data that is very strongly supported by cointegration tests; and

(4) a *time-varying relationship* between world real GDP and anthropogenic RF (i.e., the 'carbon intensity' of GDP). As I discuss below, both conceptual reasons, and overwhelming empirical evidence, support the notion that the relationship has indeed materially evolved since the mid-XIX century.

Finally,

(5) I allow for *time-variation* in trend world real GDP growth, a feature of the data that is overwhelmingly supported by Stock and Watson's (1996, 1998) tests; and

(6) I consider models in which world real GDP is either *exogenous* with respect to the rest of the system, or it is allowed to be *affected* by climate change.

My goal is to provide tentative answers to the following questions: What are the increases in temperatures and the sea level, and the decrease in ice cover, that are *already implied* by the levels of CCDs reached in 2024? How will these variables evolve going forward under alternative scenarios for the dynamics of world GDP and its carbon intensity? What are the reductions in CCDs that will be required in order to bring climate change under control? And what is the impact of climate change on world GDP?

1.1 Main results

Under an extreme scenario in which the state of the system is 'frozen' at 2024—with both the level of world GDP and its carbon intensity fixed at their 2024 values—median forecasts predict global overall temperatures (i.e. for both land and ocean) to increase by about 5.5 Celsius degrees by 2100 compared to pre-industrial times, and the sea level to increase by 53 centimeters. In order to put these numbers into perspective it is worth recalling that 5 Celsius degrees is the lower bound of the estimates for the increase in global overall temperatures associated with the so-called Paleocene-Eocene Thermal Maximum (PETM), about 55.5 million years ago. During that period Antarctica was covered with tropical forests, and Arctic waters pullulated with alligators. If global overall temperatures were to increase by 5.5 degrees compared to pre-industrial times within less than eight decades, the extent to which society could adapt—or whether it could adapt at all—is entirely open to question. Quite simply, this would be a *different planet*, far removed from the range of temperatures under which human civilizations have flourished over the last 12 to 15 thousand years.

Under an alternative scenario in which trend GDP growth remains unchanged after 2024, and the world economy fully decarbonizes by 2050, median forecasts project land and ocean temperatures and the sea level to increase by 4.9 and 2.6 degrees, and 45 centimeters respectively, compared to pre-industrial times. Further, uncertainty is substantial, thus pointing to significant upward risks: e.g., the 90%-coverage credible set for land temperatures stretches from 3.0 to 6.5 Celsius degrees. Alternative scenarios based on the same assumption for trend GDP growth and a slower pace of decarbonization, with zero carbon intensity reached in either 2075 or 2100, paint a significantly grimmer picture.

Evidence also shows that a decrease in economic growth, with trend real GDP growth falling by 1% either in 2025, or at several alternative future dates, does not materially change the overall picture, with temperatures still projected to increase by several Celsius degrees by 2100 compared to pre-industrial times. This shows that the possible future deceleration of economic growth (due e.g. to the ongoing fall in population growth) will only marginally affect climate change. The implication is that full decarbonization of GDP is the only possible solution.

Under this respect, evidence shows that, even if we were somehow able to 'freeze' JRF at its 2024 level, the intrinsic dynamics of the system will *necessarily* imply substantial increases in temperatures going forward: e.g., about 90% of the density of the forecast of land temperatures for 2100 is above the benchmark of the Paris climate agreements of 1.5 Celsius degrees, with a median projection equal to 2.5 degrees, and the upper limit of the 90 per cent-coverage credible set equal to 3.6 degrees. It is important to stress that these increases were already 'locked in' by 2024, which implies that CCDs have *already exceeded* the levels climate scientists regard as dangerous. The implication is that, in order to exit the danger zone, CCDs will have to be *brought back* to the levels that had prevailed sometimes before 2024. The obvious question is 'By how much?'. Under this respect, forecasts conditional on alternative paths for CCDs show that, given the extent of statistical uncertainty, exiting the danger zone will require bringing CCDs back to the levels of the 1970s.

Finally, evidence suggests that random variation in radiative forcing that causes a permanent increase in global overall temperatures by 1 Celsius degree is associated with a permanent decrease in world GDP by about 16%, with a 16-84% credible set stretching between -26.7% and -5.9%.

Until the 1970s, the accumulation in the atmosphere of anthropogenic sulphur emissions as a by-product of burning fossil fuels had blocked solar radiation to a significant extent, thus *mitigating* the temperature increases caused by other CCDs. This is what James Hansen has labelled as the 'Faustian bargain' our civilization has been entertaining for two centuries. Since then, the progressive removal of sulphur from the atmosphere has caused the process to go into *reverse*. As a result, since the early 1980s the evolution of the accumulated stock of sulphur emissions has contributed to an *increase* in global temperatures. Evidence suggests that even if we were somehow able to keep the other CCDs fixed at the level they reached in 2024, the complete removal of anthropogenic sulphur emissions from the atmosphere, *by itself*, would cause sizeable increases in temperatures going forward.

The paper is organized as follows. The next section discusses the data, whereas Section 3 discusses statistical evidence on their stochastic properties. Section 4 discusses my econometric approach, and Section 5 discusses the evidence: impulse-response functions to a permanent shock to the JRF index; and forecasts up to the end of the XXI century, both unconditional, and conditional on alternative possible paths for the evolution of the world GDP. Section 6 explores the impact of climate change on world GDP. Section 7 concludes.

2 The Data

Online Appendix A describes in detail the data and their sources, which are both standard in the literatures on climate science and the econometrics of climate change.

I consider nine drivers of climate change: CO2, methane (CH4), nitrous oxide (N2O), chlorofluorocarbons (CFC11 and CFC12), anthropogenic sulfur emissions (SOx), El Niño and La Niña (El Niño-Southern Oscillation, henceforth ENSO), solar irradiance, and volcanic activity. In line with the literature, I convert each individual CCD into radiative forcing (RF, expressed in Watts per square meter) based on standard formulas from physics (see Online Appendix A). Once each CCD has been converted into RF, I construct the *aggregate* JRF index as in Kaufmann, Kauppi, and Stock (2006) by summing up the individual components. As shown by Kaufmann, Kauppi, and Stock (2006, see Table II and the discussion on page 261), it is indeed not possible to reject the null hypothesis that 'the temperature effect of a unit of radiative forcing (e.g. W/m^2) is equal across forcings'. The single exception is ENSO, which I ignore for the reasons I discuss in Online Appendix A.4.[1] By the same token, I construct a corresponding index of *anthropogenic* RF, defined as the sum of the RFs of CO2, CH4, N2O, CFC11, CFC12, and SOx.

I consider indices of global[2] land and ocean temperatures, expressed in Celsius degrees. As it is routine in the literature, temperatures are expressed as 'anomalies', i.e. as *deviations* from a benchmark value. Following standard practice (see e.g. the IPCC reports) I take the average temperature over the period 1850-1900 as the benchmark, so that the temperature anomalies I work with are computed as deviations from such benchmarks.

Finally, I consider a series for world real GDP, an index of ice cover in the Northern emisphere (in million squared kilometers), and an index for the world sea level (in centimeters).

The sample period is 1850-2024.

2.1 A look at the raw data

Figure 1 shows the radiative forcing of individual climate change drivers; the JRF index minus volcanic RF, either including or excluding the radiative forcing of anthropogenic sulfur emissions (SOx); the global temperature anomalies, the world sea level, and the index of ice cover in the Northern emisphere; and either the logarithm or the growth rate of world real GDP.

[1] In brief, ENSO features virtually no spectral power at frequencies beyond 25 years, and it is extraordinarily noisy compared to the other drivers of climate change. The implication is that including the radiative forcing of ENSO in the JRF index would uniquely add a large amount of high-frequency noise, whereas it would bring essentially *no information* about the long-horizon developments that are the focus of the present work.

[2] I,.e., for the whole planet.

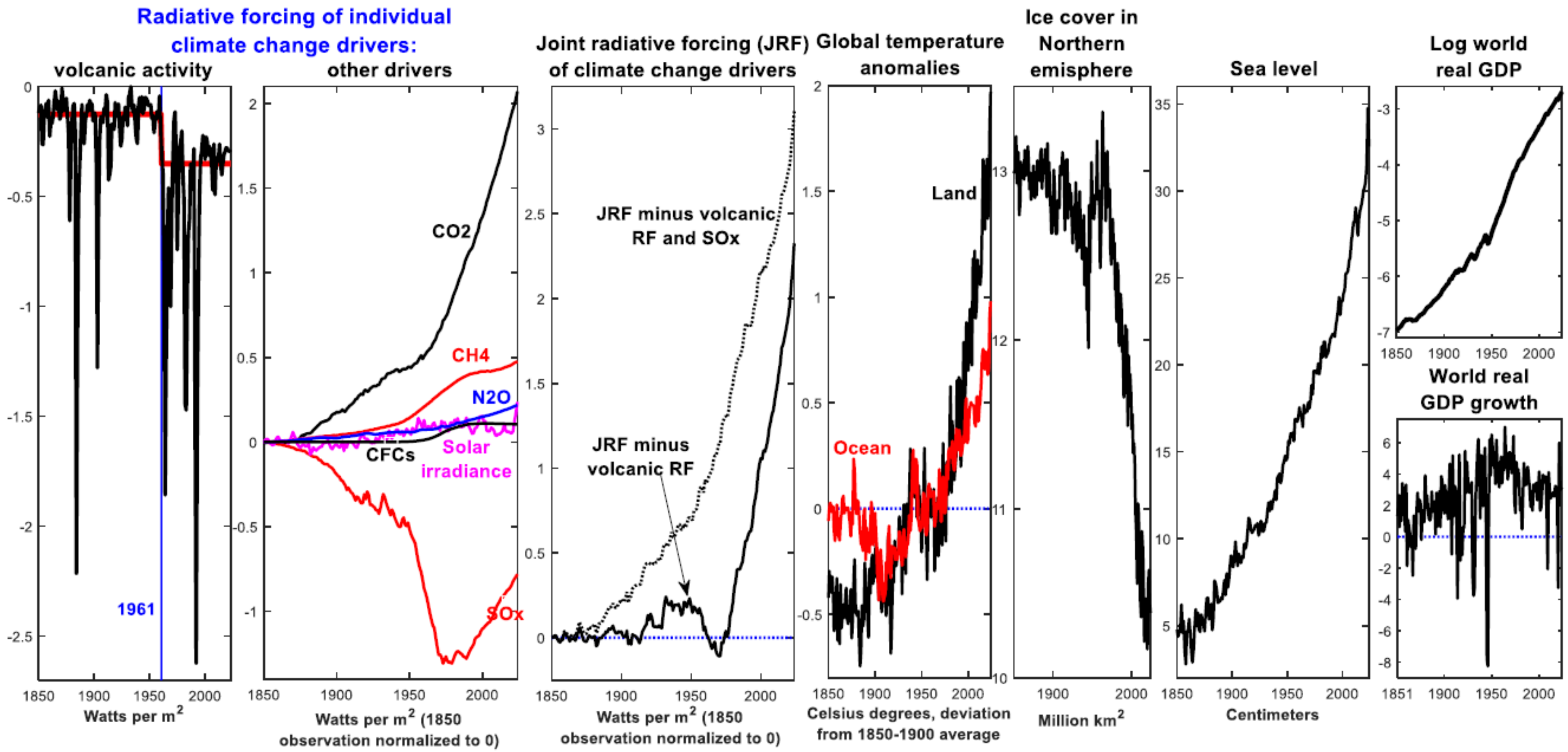

Figure 1 The raw data

Starting from the radiative forcing of the particulates injected by volcanic activity into the atmosphere, three main findings emerge from the first panel of Figure 1. First, volcanic RF is uniformly *negative*. This is because the dust spewn into the atmosphere by volcanoes prevents a fraction of solar radiation from reaching Earth in the first place, so that its impact on JRF is by definition negative. Second, volcanic RF is extraordinarily volatile, and it is manifestly characterized by a sizeable extent of heteroskedasticity. Third, although over very long periods of time[3] volcanic activity—and therefore volcanic RF—does not exhibit any trend, over comparatively short periods (such as the sample I am here working with) there are sometimes transitory shifts in the mean, due to temporary increases in volcanic activity. This is the case within the present context. A Bai and Perron (1998, 2003) test for multiple breaks at unknown points in the sample in the mean of the series plotted in the first panel of Figure 1, bootstrapped as in Diebold and Chen (1996), detects a break in 1961, with the p-values for the UD_{Max} and WD_{Max} test statistics equal to 0.050 and 0.056 respectively,[4] and the medians for the two sub-samples being equal to -0.126 and -0.351 respectively.[5] Although volcanic RF is stationary,[6] and therefore provides *no contribution* to the secular increase in JRF, this evidence illustrates why it is important to take it into account in the empirical work. First, the downward shift in the series since 1961 has had a *negative* impact on the overall JRF index, thus counteracting the impact of increases in other CCDs, and causing therefore temperatures to increase by *less* than they would otherwise. Not including volcanic RF in the model would therefore distort the evidence. In particular, since hundreds of years of data on volcanic emissions suggest that the post-1961 shift will ultimately disappear—so that the RF of other CCDs will ultimately fully reveal itself—ignoring volcanic RF would introduce a downward distortion in temperatures' forecasts. Second, the series' large volatility compared to other CCDs, together with its heteroskedasticity, suggests once again that ignoring it would likely distort the inference. In Section 4 I will discuss in detail how I model both the heteroskedasticity (via stochastic volatility) and the shift in the mean in 1961.

Turning to the other drivers of climate change, and to the aggregate indices of radiative forcing, two main findings emerge from the second and third panels of Figure 1. First, since 1850 CO2, CH4 and SOx have been by far the dominant drivers of the evolution of the JRF index. Second, until about the 1970s SOx had been playing an important moderating role in the overall increase in the JRF index. Since then, however, its previous moderating contribution has gone into reverse, as efforts to

[3]The index of volcanic activity I am working with starts in the year 1500.

[4]On the other hand, the $F_T(2|1)$ test does not detect a second break in the mean, with the bootstrapped p-value equal to 0.1496.

[5]Throughout the entire paper I focus on the medians of the two sub-samples, rather than the means, because of the significant extent of heteroskedasticity.of volcanic RF.

[6]As discussed in Section B.1 in the Online Appendix, Elliot et al.'s (1996) tests strongly reject the null of a unit root in the series, either controlling or not controlling for the identified break in the mean.

remove anthropogenic sulfur emissions from the atmosphere have started to bear fruits. As a result, over the last three decades the evolution of SOx's radiative forcing has contributed to the overall increase in the JRF index.

The third panel of Figure 1 illustrates this point in an especially stark way. Normalizing the two indices[7] to zero in 1850, excluding the impact of SOx the index would have increased much faster than it has historically been the case. To the extent that efforts to remove anthropogenic sulfur emissions from the atmosphere will continue and will be successful, the radiative forcing of SOx shown in the second panel will converge to zero, and the overall JRF index will therefore be more and more dominated by the remaining drivers. The implications of this are sobering. As shown in the third panel, if in 2024 we had somehow been able to remove SOx from the atmosphere, the normalized JRF excluding volcanic RF would have shot up from about 2.7 to 3.2. The implication is stark. Even if we were able to keep the non-SOx radiative forcing fixed at the level reached in 2024, efforts to clean up the atmosphere of SOx, *by themselves*, automatically imply sizeable increases in temperatures going forward.

A similar point holds for volcanic eruptions. As previously mentioned, although over very long periods of time the amount of particulates injected into the atmosphere by volcanic eruptions does not show any trend, in a few instances—such as over the period since 1961—it exhibits a clear shift in the mean. Exactly as for SOx, the fact that since the early 1960s volcanic RF has been *more negative* than it had been before implies that, to the extent that the pre-1961 pattern of eruptions will ultimately reassert itself, global temperatures will *necessarily* increase by non-negligible amounts even in the absence of any change in the other drivers of radiative forcing. In particular, if the median volcanic RF were to revert back to its pre-1961 value of -0.126, in Europe temperatures would increase by 0.22 Celsius degrees.[8]

This, together with the previous discussion about the impact of cleaning up the atmosphere of SOx, shows that even without further increases in the drivers of climate change, there is already, deeply embedded in the system-Earth, a sizeable amount of *committed warming*, i.e. future temperature increases that are already 'baked in the cake' and impossible to avoid other than by removing carbon from the atmosphere, geoengineering, etc. As we will see in Section 5.4, due to the comparatively long lags with which global temperatures increase following an increase in radiative forcing, there is in fact additional committed warming already embedded in the system-Earth.

The fourth, fifth, and sixth panels provide a stark illustration of the main features of the global heating phenomenon, with dramatic increases in temperatures and the sea level since 1850, and a marked shrinkage of the ice surface in the Northern

[7] We exclude from both indices volcanic RF (i.e., the series plotted in the first panel), because its large volatility compared to other RF series would make the two indices very noisy. This is without any loss of generality, since volcanic activity is stationary.

[8] This is because the cointegration vector between the temperature anomaly for the European continent and the JRF index is indistinguishable from $[1\ {-1}]'$. This evidence is available upon request.

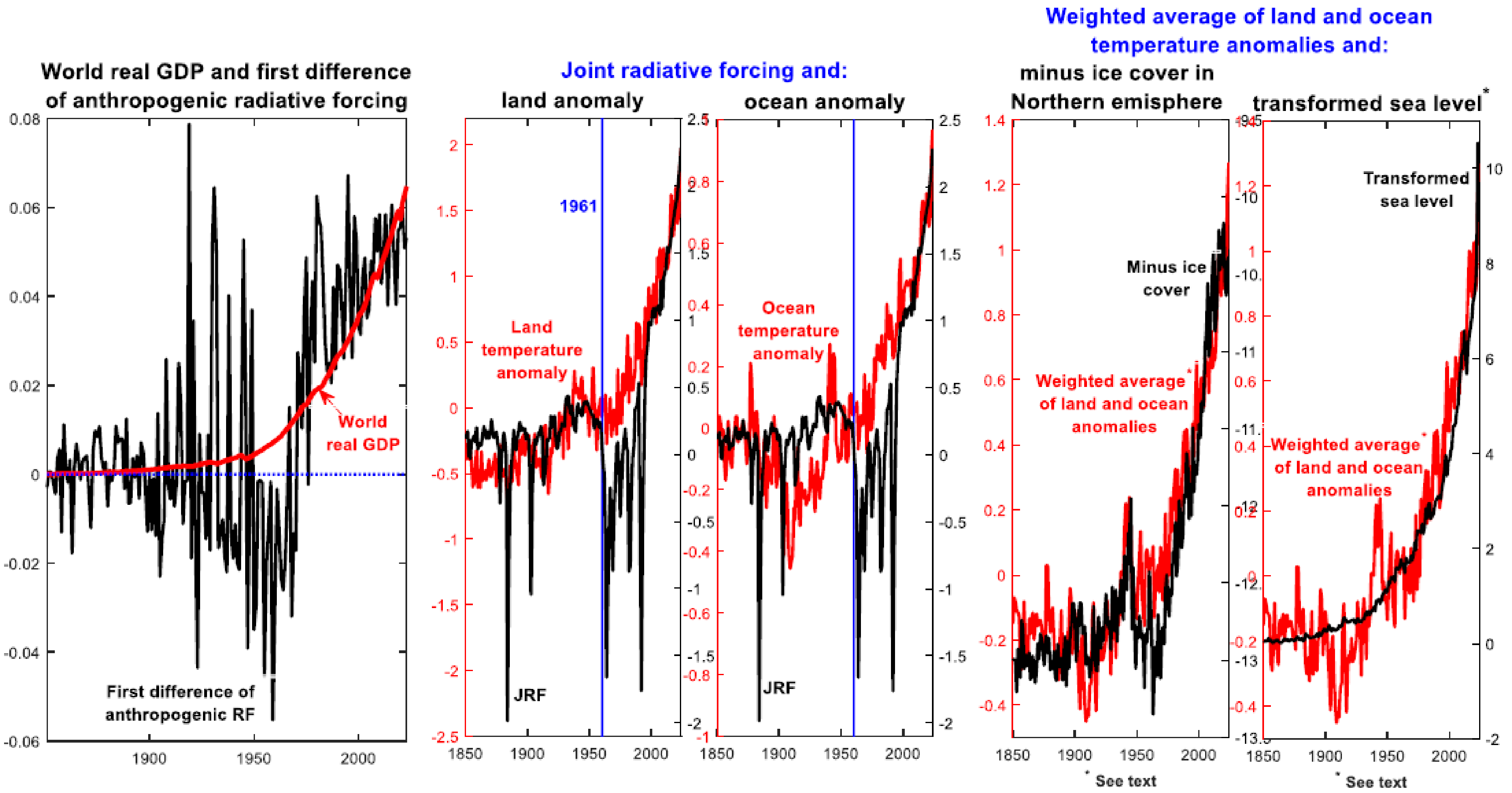

Figure 2 The long-run equilibrium relationships

emisphere. Further, the phenomenon has clearly accelerated over the most recent decades. This is especially clear for temperatures and ice cover, and less so for the sea level (as I discuss below, in the long run the sea level approximately evolves with the cubic root of global temperatures).

Finally, the last two panels, especially the bottom one, highlight sizeable changes in the growth rate of world real GDP since 1850, with average growth first progressively increasing up until the 1960s-1970s, then decreasing, and finally seemingly stabilizing at about 2-3 per cent.

2.2 The long-run equilibrium relationships

Figure 2 illustrates the long-run equilibrium (i.e., as we will see, *cointegration*) relationships that are embedded in the system. The first panel shows the relationship between the *level* (not the logarithm) of world real GDP and the *first difference* of anthropogenic RF, which as discussed in Section 2 is defined as the sum of the RFs pertaining to CO2, CH4, N2O, CFC11, CFC12, and SOx. The reason why the long-run relationship pertains to the level of the former series and the first difference of the latter is straightforward. Every year, in order to produce a certain amount of real output, the world economy uses a corresponding amount of energy. This translates into corresponding *new emissions* of CO2, CH4, etc., which add to the *existing stocks* of anthropogenic CCDs.[9] In turn, this leads to a progressive increase, year after year, in the level of anthropogenic RF, which is the fundamental driver of climate change. The implication is that, both as a matter of logic, and in practice, the relationship pertains to the level of world real GDP, and the change in (i.e. the first difference of) the anthropogenic RF index.

Two things are apparent from the first panel of Figure 2. First, in the long-run the two series tend indeed to closely co-move. Second, in the short-to-medium run they tend however to deviate from each other. Although most of these deviations are quite short-lived, and they can therefore be thought of as 'noise' contaminating the fundamental relationship determined by the 'carbon intensity' of GDP, the period between the 1930s and the end of the 1970s clearly appears different from the rest of the sample, with a persistent *negative* change in anthropogenic RF. As it is apparent from the second panel of Figure 1, this was caused by a dramatic increase in the amount of SOx during that period. Then, starting from the 1970s, SOx first peaked, and then started being removed from the atmosphere, with the result that the positive relationship between world real GDP and the first difference of anthropogenic RF reasserted itself. In Section B.3 in the Online Appendix I show that the two series are indeed cointegrated.

[9] To be precise, each CCD has a certain *half-life* in the atmosphere. E.g. the half-life of CO2 is about 120 years, whereas that of methane is about 10.5 years. The fact that the dominant CCD, CO2, has such a long half-life implies that although strictly speaking shocks to anthropogenic RF are ultimately transitory, for practical purposes they can be regarded as permanent.

The second and third panels of Figure 2 shows the long-run relationships between the JRF index and the global land and ocean temperature anomalies. The long-run equilibrium relationships between the series are quite clearly apparent. Notice that the previously discussed downward shift in the mean of volcanic RF in 1961 caused a temporary divergence between the JRF index and temperatures. However, since volcanic RF, although subject to infrequent and temporary shifts in the mean, is stationary, the long-run relationship between JRF and the two temperatures series ultimately reasserted itself. Again, in Section B.3 in the Online Appendix I show that the JRF is indeed cointegrated with temperature anomalies.

The fourth panel shows the long-run relationship between a weighted average of land and ocean temperatures and *minus* the ice cover in the Northern emisphere. I compute the weighted average as $T^* = \alpha T_{\text{Land}}+(1\text{-}\alpha)T_{\text{Ocean}}$, where the notation is obvious, and α is computed by minimizing the sum of $(T^*\text{-}T_{\text{Overall}})^2$, where T_{Overall} is the global overall (i.e. both land and ocean) temperature anomaly. The estimated value of α is 0.2994. The figure speaks for itself, and it clearly points towards cointegration between the two series, a feature of the data that is strongly supported by statistical tests.

Finally, the last panel shows the long-run relationship between the weighted average of land and ocean temperatures and a *non-linear transformation* of the sea level series. Evidence indeed quite clearly suggests that, in the long run, the sea level approximately evolves with the cubic root of global temperatures. In particular, the best fit is provided by an exponent equal to 2.94, rather than exactly 3. The transformed sea level series plotted in the last panel of Figure 2 is therefore equal to the 'raw' sea level series raised to the power of 2.94. Again, the evidence speaks for itself, and it strongly suggests that in the long run the two series in the panel, once appropriately rescaled, move one-for-one.

3 Stochastic Properties of the Data

Online Appendix B features an extensive analysis of the stochastic properties of world GDP and climate change series, based on unit root and cointegration tests; tests for breaks in the mean; and Stock and Watson's (1996, 1998) tests of the null of time-invariance in the Data Generation Process (DGP) for the first differences[10] of individual series, against the alternative of random-walk time-variation in the mean. Overall, evidence strongly and consistently suggests that

(1) in line with the evidence in Figure 1, trend world real GDP growth has exhibited a significant extent of time-variation over the sample period.

(2) Solar irradiance has evolved essentially as a random-walk with drift, reflecting its well-known long-run secular increase, whereas volcanic RF has been very strongly stationary, either controlling or not controlling for the identified break in the mean.

[10]Since volcanic RF is I(0), for this series I consider the level.

Except for volcanic RF's heteroskedasticity, there is no evidence of time-variation in the stochastic properties of either series.

(3) Temperature anomalies, the transformed sea level, the ice cover series, and anthropogenic RF are all I(2). In particular, their first differences feature a random-walk component that is very strongly and uniformly detected across the board by Stock and Watson's (1996, 1998) tests.

(4) In line with previous cointegration-based studies of climate change, the levels of the JRF index and of temperature anomalies are cointegrated. As mentioned, this is in fact what physics predicts it should be. By the same token, the level of world GDP is cointegrated with the first difference of anthropogenic radiatiave forcing.

(5) Global temperatures are cointegrated with either ice cover, or the transformed sea level series.

Since evidence is near-uniformly very strong and consistent, in this section I do not discuss it in detail. The interested reader is referred to Online Appendix B for a detailed discussion of both technical details, and the evidence itself.

Intuitively, the reason for the presence of time-variation in the means of the first differences of temperature anomalies, the sea level, ice cover, and anthropogenic RF is straightforward. The system-Earth went from a period, before the Industrial Revolution, characterized by virtually no economic growth—and therefore negligible emissions of anthropogenic CCDs—to the subsequent period characterized by the progressive spreading of economic growth across the globe. As an increasing number of countries experienced sustained growth, their emissions of CCDs increased accordingly. The consequence of this is the progressive *long-term acceleration* in the rate of overall increase of CCDs. A second main reason for such acceleration is the fact that, as mentioned, until the 1970s the accumulation of anthropogenic sulphur emissions in the atmosphere partly mitigated the impact of increases in the other CCDs. Since then, however, the progressive removal of sulphur has thrown this process into reverse. This implies that the rate of change of the *joint* impact of all CCDs, as captured by the JRF index, has exhibited a non-negligible extent of variation over the sample period.

I now turn to discussing my econometric approach.

4 The Econometric Approach

In this section I discuss the benchmark model I use throughout most of the paper, in which the evolution of world real GDP is assumed to be unaffected by global warming. In Section 6 I will discuss how the benchmark model is modified in order to take into account of a possible impact of temperatures on GDP.

4.1 The benchmark model

4.1.1 Exogenous drivers of climate change

World real GDP Based on the evidence from Stock and Watson's (1996, 1998) tests reported in Section B.2 in the Online Appendix, I assume that the time-varying mean of the log-difference of world real GDP, μ_t, evolves as a random walk:

$$\mu_t = \mu_t + \epsilon_t^{\mu}, \tag{1}$$

with $\epsilon_t^{\mu} \sim N(0,\, \sigma_{\mu}^2)$. The deviation from μ_t of the log-difference of GDP, $\Delta y_t = \Delta \ln GDP_t$, is then postulated to evolve as an AR(p) process,

$$\Delta y_t - \mu_t = \phi_1(\Delta y_{t-1} - \mu_{t-1}) + ... + \phi_p(\Delta y_{t-p} - \mu_{t-p}) + \epsilon_t^{\Delta y} \tag{2}$$

with $\epsilon_t^{\Delta y} \sim N(0,\, \sigma_{\Delta y,t}^2)$, where $\sigma_{\Delta y,t}^2$ is a time-varying variance which, as I discuss below, is postulated to evolve according a stochastic volatility specification.

Volcanic radiative forcing Based on the evidence from Elliot et al.'s (1996, 1998) and Stock and Watson's (1996, 1998) tests reported in Section B.2 in the Online Appendix, I assume that the deviation from its mean of the *level* of volcanic RF, RF_t^V, follows an AR(p) process,

$$RF_t^V - \delta_t = \psi_1(RF_{t-1}^V - \delta_{t-1}) + ... + \psi_p(RF_{t-p}^V - \delta_{t-p}) + \epsilon_t^V \tag{3}$$

with δ_t equal to either δ_1, before 1961, or δ_2, after that, and with $\epsilon_t^V \sim N(0,\, \sigma_{V,t}^2)$, with $\sigma_{V,t}^2$ being a time-varying variance.

Solar radiative forcing By the same token, I assume that the *first difference* of solar RF, ΔRF_t^S, also follows an AR(p) process,

$$\Delta RF_t^S - \xi = \varphi_1(\Delta RF_{t-1}^S - \xi) + ... + \varphi_p(\Delta RF_{t-p}^S - \xi) + \epsilon_t^S \tag{4}$$

with $\epsilon_t^S \sim N(0,\, \sigma_{S,t}^2)$.

4.1.2 Long-run equilibrium relationships

Based on the evidence from Wright's (2000) tests reported in Section B.3 in the Online Appendix, I assume that the level of the land and ocean temperature anomalies is cointegrated with the level of the JRF index, so that in a long-run equilibrium

$$JRF = \alpha_x T_x \tag{5}$$

where JRF is the JRF index, T_x with $x =$ Land, Ocean is either temperature anomaly, and α_x is the cointegration coefficient.

I also assume that in a long-run equilibrium the change in anthropogenic RF, ΔRF_t^A, is a function of the level (not the logarithm) of world GDP, GDP_t, through a coefficient of 'anthropogenic RF intensity' (or 'carbon intensity', as a shorthand) of GDP, β_t,

$$\Delta RF_t^A = \beta_t GDP_t \tag{6}$$

In line with the discussion in Section 2.1, I assume that β_t evolves as a random walk,

$$\beta_t = \beta_t + \epsilon_t^\beta, \tag{7}$$

with $\epsilon_t^\beta \sim N(0,\, \sigma_\beta^2)$. The rationale for this specification is the following. Anthropogenic RF is defined as the sum of the radiative forcing of CO2, methane, nitrous oxide, chlorofluorocarbons, and anthropogenic sulphur emissions. Due to technological progress, since 1850 the amount of anthropogenic CCDs emitted for one unit of world GDP has changed quite significantly. E.g., in the XIX century energy was produced mainly by burning carbon, whereas in the XX century the world economy mostly switched to oil, and in recent years partly to renewables. Further, as discussed, the progressive cleaning up of the atmosphere from sulphur emissions since the 1970s has injected a further element of time-variation in the relationship between GDP and anthropogenic RF.

Finally, in line with the evidence in the last two panels of Figure 2, I assume that the weighted average of land and ocean temperatures is cointegrated with either minus the ice cover, or the transformed sea level series, so that in a long-run equilibrium

$$T^* = \gamma_S S = \gamma_I I \tag{8}$$

where S and I are the the transformed sea level and ice cover series, and γ_S and γ_I are their respective cointegration coefficients.

4.1.3 The structural VAR representation

I assume that conditional on the paths of the exogenous processes—μ_t, Δy_t, RF_t^V, ΔRF_t^S, and β_t—the evolution of the system is fully characterized by a *structural VAR* (SVAR) representation for

(1) the cointegration residuals between the JRF index and land and ocean temperature anomalies;

(2) the cointegration residuals between the weighted average of land and ocean temperatures and either ice cover or the transformed sea level index; and

(3) the deviation of the change in anthropogenic RF from its equilibrium with world GDP implied by (6).

Assuming, for illustrative purposes, a SVAR with one lag, the dynamics of the system is characterized by

$$
\underbrace{\begin{bmatrix} \Delta y_t - \mu_t \\ \Delta RF_t^A - \beta_t GDP_t \\ JRF_t - \alpha_{\mathrm{L}} T_t^{\mathrm{L}} \\ JRF_t - \alpha_{\mathrm{O}} T_t^{\mathrm{O}} \\ T_t^* - \gamma_I I_t \\ T_t^* - \gamma_S S_t \\ RF_t^V - \delta_t \\ \Delta RF_t^S - \xi \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} x & & & & & & & \\ x & x & x & x & x & x & & \\ x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x \\ & & & & & & x & \\ & & & & & & & x \end{bmatrix}}_{B_1} \underbrace{\begin{bmatrix} \Delta y_{t-1} - \mu_{t-1} \\ \Delta RF_{t-1}^A - \beta_{t-1} GDP_{t-1} \\ JRF_{t-1} - \alpha_{\mathrm{L}} T_{t-1}^{\mathrm{L}} \\ JRF_{t-1} - \alpha_{\mathrm{O}} T_{t-1}^{\mathrm{O}} \\ T_{t-1}^* - \gamma_I I_{t-1} \\ T_{t-1}^* - \gamma_S S_{t-1} \\ RF_{t-1}^V - \delta_{t-1} \\ \Delta RF_{t-1}^S - \xi \end{bmatrix}}_{Y_{t-1}} +
$$

$$
+ \underbrace{\begin{bmatrix} 1 & & & & & & & \\ + & 1 & & & & & & \\ + & + & 1 & & & & + & + \\ + & + & x & 1 & & & + & + \\ + & + & x & x & 1 & & + & + \\ + & + & x & x & x & 1 & + & + \\ & & & & & & 1 & \\ & & & & & & & 1 \end{bmatrix}}_{A_0} \underbrace{\begin{bmatrix} \epsilon_t^{\Delta y} \\ \epsilon_t^{A} \\ \epsilon_t^{LOSI} \\ \epsilon_t^{OSI} \\ \epsilon_t^{SI} \\ \epsilon_t^{S} \\ \epsilon_t^{V} \\ \epsilon_t^{S} \end{bmatrix}}_{\epsilon_t} \tag{9}
$$

where A_0 is the impact matrix of the structural shocks; '+' labels a non-negative scalar; 'x' is a non-0 scalar on which no sign restriction is imposed; T_t^{L} and T_t^{O} are the land and ocean temperature anomalies, and α_{L} and α_{O} are the respective cointegration coefficients with the JRF index; and all entries in either B_1 or A_0 that are not labelled as '1', '+', or 'x' are equal to 0. ϵ_t^A is a shock capturing variation in anthropogenic radiative forcing over and above that due to changes in the level of world real GDP. As such, it captures a wide range of phenomena, the most important of which is a sizeable portion of the secular variation in the stock of anthropogenic sulfur emissions. When SOx is removed from the atmosphere anthropogenic RF increases, whereas the impact on world real GDP is negligible to *nil*. ϵ_t^{LOSI}, ϵ_t^{OSI}, ϵ_t^{SI}, and ϵ_t^{I} are four orthogonalized shocks that do not have any specific interpretation. On impact ϵ_t^{LOSI} only affects land and ocean temperatures, ice cover, and the sea level; ϵ_t^{OSI} only affects ocean temperatures, ice cover, and the sea level; ϵ_t^{SI} only affects ice cover and the sea level; and ϵ_t^{S} only affects the sea level. Since neither shock has any clear interpretation, in what follows I will ignore them.

The matrices B_1 and A_0 encode the exogenous evolution of $\Delta y_t - \mu_t$, $RF_t^V - \delta_t$ and $\Delta RF_t^S - \xi$, each one uniquely as a function of its own lags and its own shocks. Further, B_1 assumes that the deviation of anthropogenic RF from its technology-dictated long-run equilbrium, $\Delta RF_t^A - \beta_t GDP_t$, is not affected by either volcanic or solar RF. The rationale for this is that $\Delta RF_t^A - \beta_t GDP_t$ hinges on technological relationships, and as such it should therefore have nothing to do with either volcanic or solar activity.

For each draw from the posterior distribution of the model's parameters, I impose the following restrictions on the IRFs of the four shocks I am interested in, $\epsilon_t^{\Delta y}$, ϵ_t^A, ϵ_t^V, and ϵ_t^S:

- a positive $\epsilon_t^{\Delta y}$ produces non-negative IRFs at all horizons for GDP, anthropogenic RF, JRF, global temperatures, the sea level, and ice cover.
- Positive ϵ_t^A, ϵ_t^V, and ϵ_t^S produce non-negative IRFs at all horizons for anthropogenic RF, volcanic RF, and solar RF respectively. Any of the three shocks produces non-negative IRFs at all horizons for JRF, global temperatures, the sea level, and ice cover.

Finally, for each draw from the posterior distribution I impose the restriction that a unitary increase in JRF due to any of the four shocks produces the *same impulse vector* at t=0 for temperatures, sea level, and ice cover. That is, if ΔJRF$_0$=1 in response to either $\epsilon_t^{\Delta y}$, ϵ_t^A, ϵ_t^V, or ϵ_t^S, then $\Delta T_0=a$, nd$\Delta S_0=b$, and $\Delta I_0=-c$ for any of the four shocks, with a, b, c>0. The rationale is the same that justifies aggregating the radiative forcing of individual climate change drivers into a single index, the JRF. As previously discussed, evidence suggests that the *specific source* of radiative forcing is irrelevant. In particular, as shown by Kaufmann, Kauppi, and Stock (2006, see Table II and the discussion on page 261), it is not possible to reject the null hypothesis that '*the temperature effect of a unit of radiative forcing (e.g. W/m^2) is equal across forcings*'.

4.1.4 Estimation

I estimate all models via Bayesian methods, based on a straightforward adaptation to the problem at hand of the Metropolis-within-Gibbs algorithm proposed by Justiniano and Primiceri (2008) to estimate DSGE models with stochastic volatility. The algorithm is described in detail in Online Appendix D. In this sub-section I only briefly describe its main features.

Justiniano and Primiceri's (2008) algorithm (see their Appendix A) consisted of two 'blocks' of steps. In Block I the stochastic volatilies of the structural disturbances, and their hyper-parameters, were drawn conditional on the parameters of the DSGE models via a Gibbs step. In Block II a Metropolis step was used in order to draw the DSGE model's parameters conditional on the stochastic volatilities. Within the present context, in Block II, instead of drawing the parameters of the DSGE models, I draw the parameters of the VAR (9), again via a Metropolis step. As for step I, the only difference with Justiniano and Primiceri (2008) is that I use a simpler specification for the stochastic volatilities. Instead of using their mixture of distributions, I postulate that any of the volatilities of the structural innovations evolves as in Jacquier, Polson, and Rossi (2002).

I run a burn-in pre-sample of 1,000,000 draws which I then discard. I then generate 10,000,000 draws, which I 'thin' by sampling every 1,000 draws in order to reduce their autocorrelation. This leaves 10,000 draws from the ergodic distribution which I use for inference. For all models the fraction of accepted draws is very close to the ideal one, in high dimensions, of 0.23 (see Gelman, Carlin, Stern, and Rubin, 1995). I check convergence of the Markov chain based on Geweke's (1992) inefficiency factors (IFs) of the draws from the ergodic distribution for each individual parameter. For all parameters the IFs are equal to at most 3-4, well below the values of 20-25 which are typically taken to indicate problems in the convergence of the Markov chain.

4.1.5 Restrictions imposed in estimation

In estimation I impose the restrictions that, for each parameters' draw from the posterior distribution, shocks generating permanent increases in either anthropogenic RF (i.e., $\epsilon_t^{\Delta y}$ and ϵ_t^A), or the RF of solar irradiance (ϵ_t^S), generate non-negative IRFs at all horizons for the respective series, i.e. anthropogenic RF and the RF of solar irradiance, respectively. Finally, I restrict the response of volcanic RF to volcanic RF shocks (ϵ_t^V) to be negative at all horizons.

5 Evidence

5.1 Trend GDP growth and the relationship between GDP and anthropogenic emissions

The first panel of Figure 3 shows world real GDP growth and the two-sided median estimate of its time-varying trend μ_t, together with the 16-84 and 5-95 per cent credible sets of the posterior distribution. The estimate of μ_t has been computed via the Monte Carlo integration procedure proposed by Hamilton (1986). Based on the median estimate, trend growth had progressively increased from about 1.5% in the 1850s to slightly more than 2% in the aftermath of WWII; it had further accelerated, reaching a peak of about 3.5% in the mid-1960s; and it has decreased ever since, reaching about 2.5% at the end of the sample.

The remaining two panels of Figure 3 show either the one- or the two-sided median estimates of the anthropogenic RF intensity of GDP, i.e. β_t, together with their 16-84 and 5-95 per cent credible sets. Consistent with the evidence in the second and third panels of Figure 1, until WWI the *negative* impact on anthropogenic RF of the accumulation of sulphur emissions in the atmosphere roughly balanced out the *positive* impact of the remaining anthropogenic CCDs. As a result, as shown in the third panel of Figure 1, the JRF index *net* of the impact of volcanic emissions had remained essentially constant. Since solar irradiance plays a minor role, this implies that anthropogenic RF had also remained virtually unchanged between the mid-XIX century and WWI. This is why the one-sided estimate in the second panel of

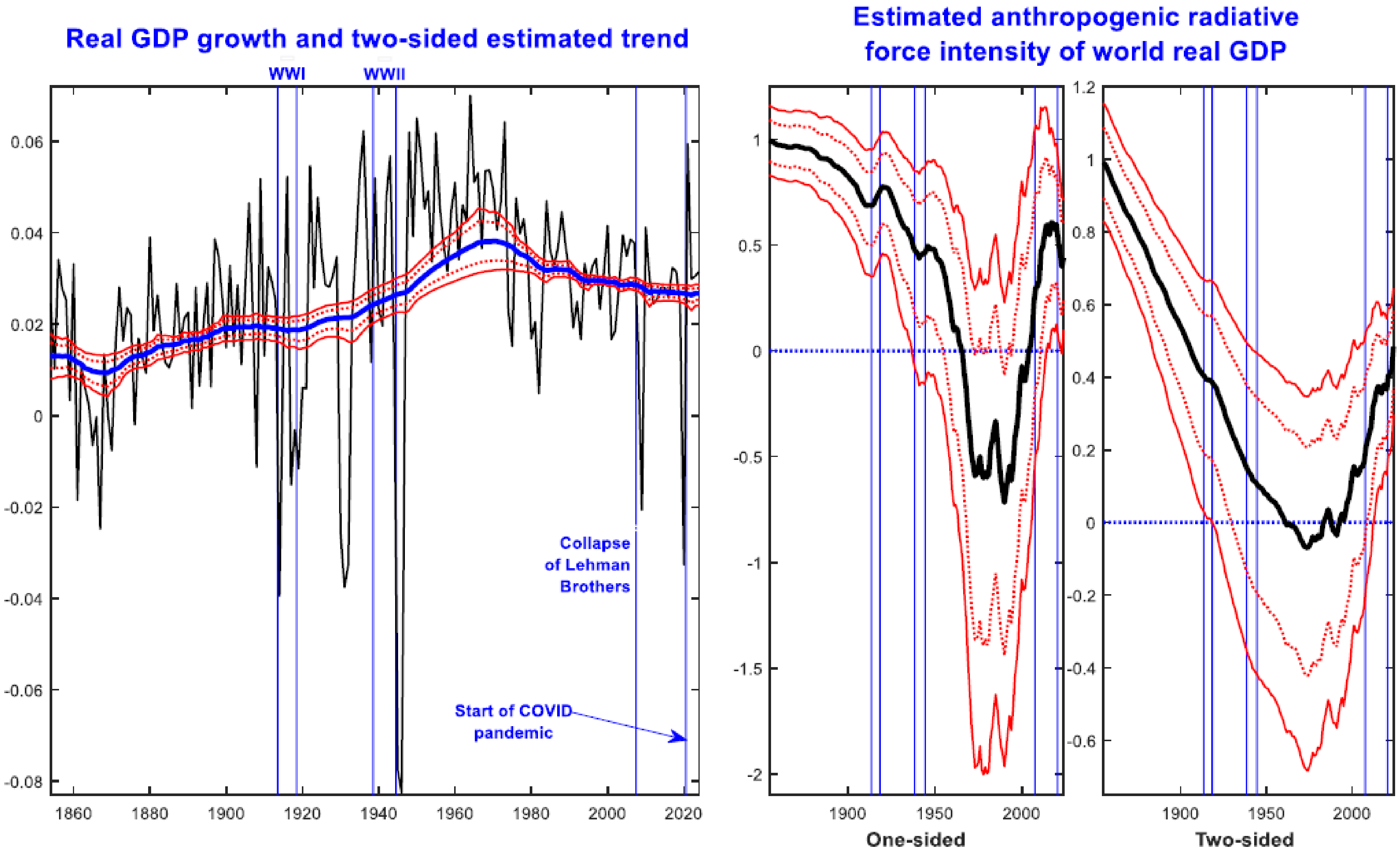

Figure 3 World real GDP growth and two-sided estimate of its trend, and one- and two-sided estimates of the anthropogenic radiative force intensity of GDP (median, and 16-84 and 5-95 credible set)

Figure 3 exhibits modest variation until WWI. Between the aftermath of WWII and the 1970s, on the other hand, the accumulation of sulphur emissions had dominated other anthropogenic CCDs, with the result that the anthropogenic RF intensity of GDP had fallen below zero. This is consistent with the fact that, in the third panel of Figure 1, the JRF index net of volcanic emissions had decreased during those years. Finally since the 1980s the removal of sulphur from the atmosphere contributed to the increase in anthropogenic RF, with the result that anthropogenic RF intensity has dramatically shot up.

5.2 The volatilities of the structural shocks

Figure 4 shows the estimated standard deviations of the eight identified structural disturbances. For three of them—the shock to solar RF, and the residual orthogonalized shocks to ice cover the sea level, and either both temperature anomalies, or just the ocean anomaly—the volatility has been virtually unchanged over the entire sample period. At the other extreme, in line with the evidence in the first panel of Figure 1, the volatility of shocks to volcanic RF has exhibited a dramatic extent of variation, which closely mirrors the negative spikes in Figure 1. The standard deviation of innovations to real GDP growth exhibits a roughly hump-shaped pattern, with an increase starting from the early XX century, a peak around World War II, and a sharp fall in the 1950s. Starting from the early XXI century, the shocks of the financial crisis and then of the COVID pandemic have led to a progressive increase. Finally, the standard deviation of the residual shock to anthropogenic RF (i.e. ϵ_t^A) exhibits an even clearer hump-shaped pattern, with a peak reached roughly around World War I.

5.3 Impulse-response functions to radiative forcing shocks

Figure 5 shows the series' IRFs to radiative forcing shocks. For each draw from the posterior distribution I normalize the IRFs to either anthropogenic or solar RF shocks by the long-run impact on anthropogenic and solar RF, respectively. On the other hand, since volcanic RF shocks are transitory, I normalize their IRFs by the impact on volcanic RF at t=0.

Following an exogenous shock to anthropogenic RF, i.e. ϵ_t^A, anthropogenic RF itself essentially reaches its new long-run equilibrium in about two decades, whereas the response of temperatures, the sea level and ice cover is more drawn out and inertial.

As one would expect from the first panel of Figure 1, the response of volcanic RF to ϵ_t^V reverts to zero very quickly, in slightly more than ten years. The responses of temperatures and ice cover are significant on impact, but they quickly become insignificant just a few years later. As for the sea level, it is barely significant even on impact.

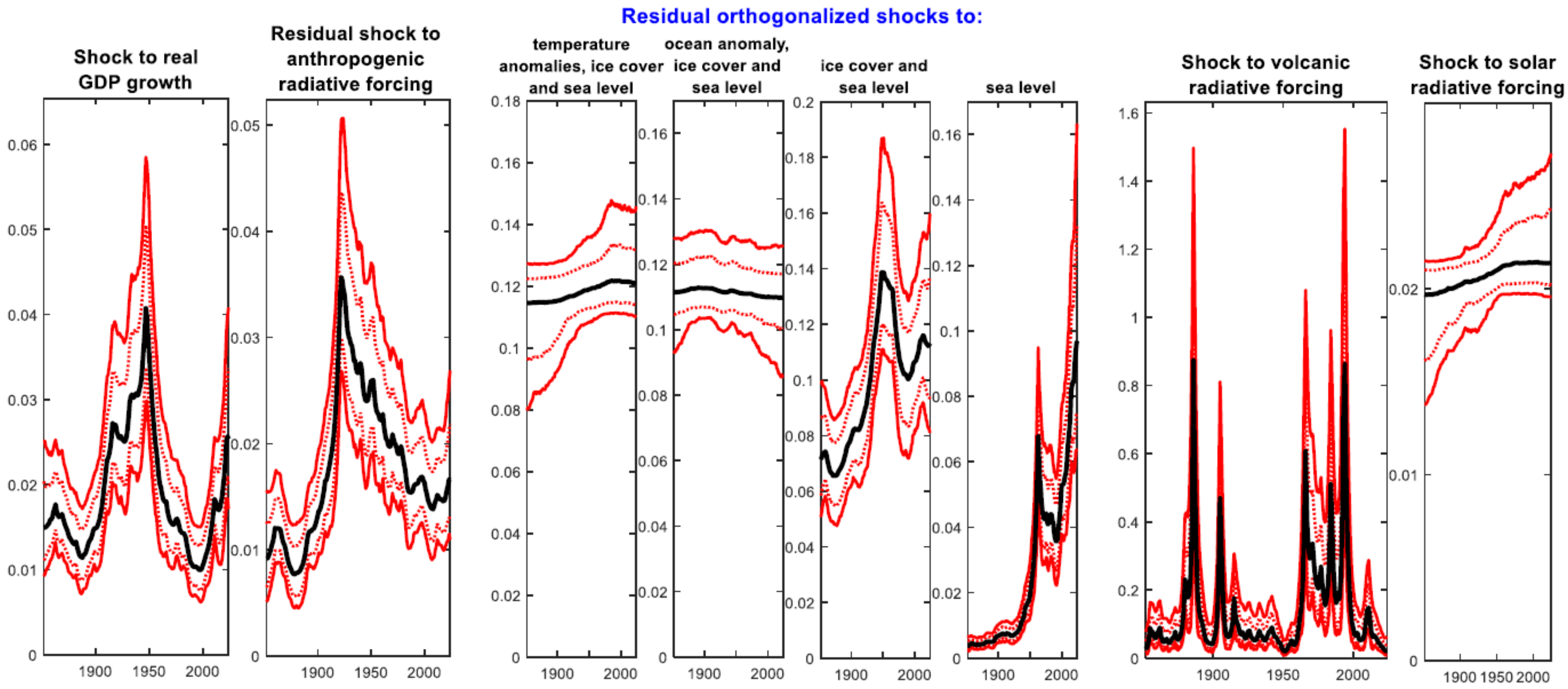

Figure 4 Estimated standard deviations of structural shocks (median, and 16-84 and 5-95 credible sets)

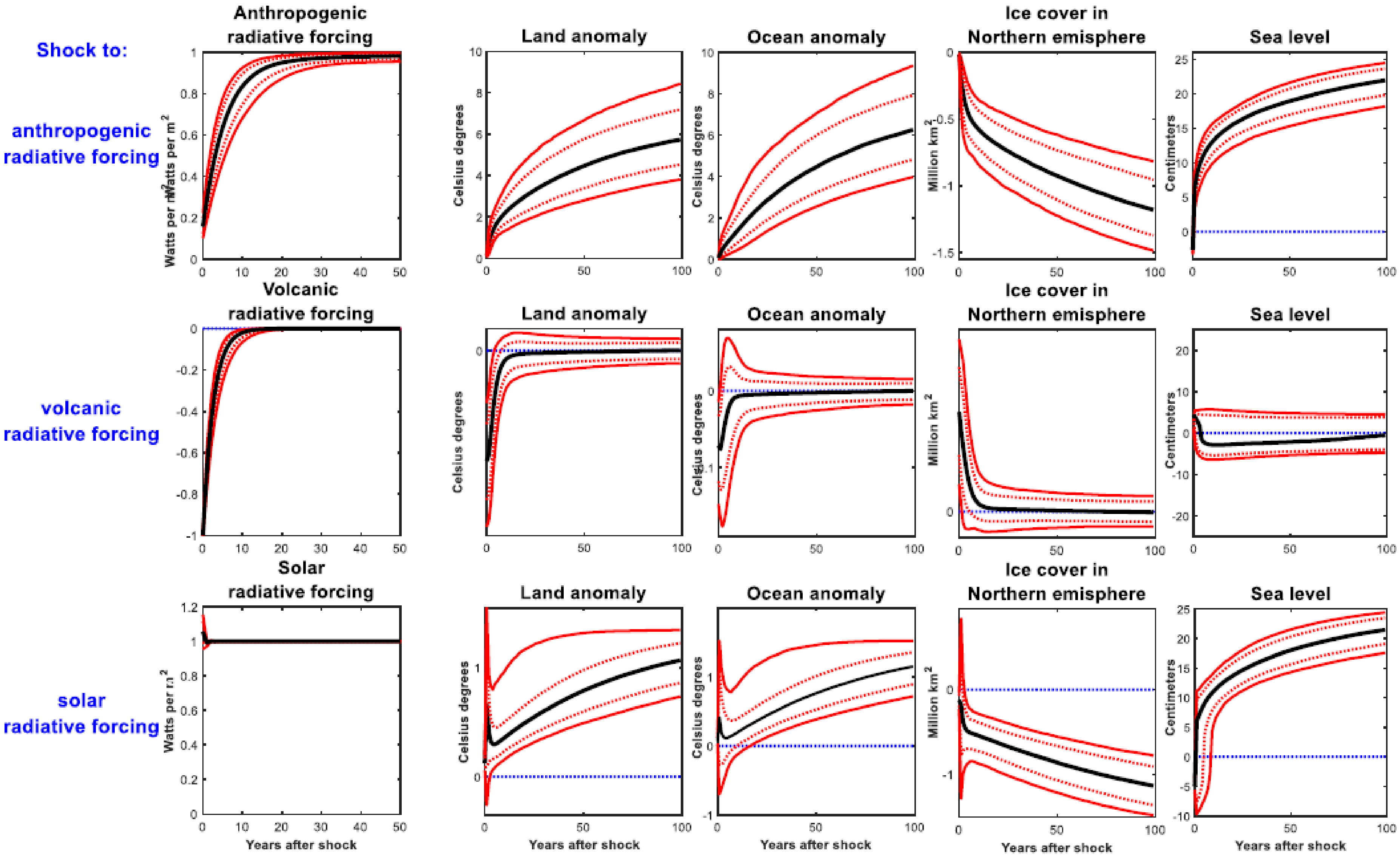

Figure 5 Impulse-response functions to the three identified shocks to radiative forcing (median, and 16-84 and 5-95 credible set)

Finally, the response of solar RF to ϵ_t^S is virtually flat at all horizons, thus showing that this series is essentially a pure unit root process. The responses of temperatures, ice cover and the sea level are, as expected, drawn out, although with a different profile from the IRFs to ϵ_t^A.

5.4 Unconditional forecasts under 'no change' scenarios

Figure 6 shows evidence from the following exercise. I 'freeze' the state of the system—in particular, both the level of GDP, and the estimate of β_t—at 2024, and I then stochastically simulate the model forward until the end of the XXI century. The evidence from this exercise is sobering. Under such 'no change' scenario, median forecasts predict the land and ocean temperature anomalies to reach nearly 8 and about 4.2 Celsius degrees by 2100, respectively, with the 90%-coverage credible set equal to [4.9; 11.0] and [2.7; 6.0] degrees. The forecasts for the sea level and ice cover are equally ominous, with the median projection for the former reaching 53 centimeters in 2100, and the 90%-coverage credible set for the latter stretching below zero—i.e., *no ice in the Northern emisphere*—at the end of the century.

5.5 Forecasts conditional on alternative assumptions about the evolution of GDP and anthropogenic RF intensity

Figure 7 shows evidence from the following exercise. I 'freeze' once again the state of the system at 2024, and I then stochastically simulate the model forward until the end of the XXI century (1) keeping GDP at its 2024 level, and (2) assuming *full decarbonization* of the world economy in 2025. The evidence from the exercise is sobering. Even if we were somehow able to prevent *any* increase in anthropogenic RF after 2024, still, the intrinsic dynamics of the system in response to past JRF increases would produce dangerous levels of warming going forward, with corresponding impacts on sea level and ice cover. Focusing on land temperatures, about 90% of the density of the forecast for 2100 is above the benchmark of the Paris climate agreements of 1.5 Celsius degrees, with a median projection equal to 2.5 degrees, and the upper limit of the 90 per cent-coverage credible set equal to 3.6 degrees. It is important to stress that these increases were already 'locked in' by 2024, which implies that CCDs have *already exceeded* the levels climate scientists regard as dangerous. In turn this implies that only bringing the JRF *back* to levels reached sometime before 2024 would allow to bring climate change under control. The obvious question is by how much should the JRF decrease. Figures 8 and 9 provide some tentative answers to this question.

Figure 8 shows shows evidence from the following exercise. I 'freeze' trend GDP growth, μ_t, to the estimated value for 2024, and I then simulate the model forward until 2100 conditional on three alternative scenarios for the evolution of anthropogenic RF intensity, in which after 2024 β_t decreases linearly, reaching zero in either 2050, 2075, or 2100. Even the best-case scenario, in which full decarbonization is achieved

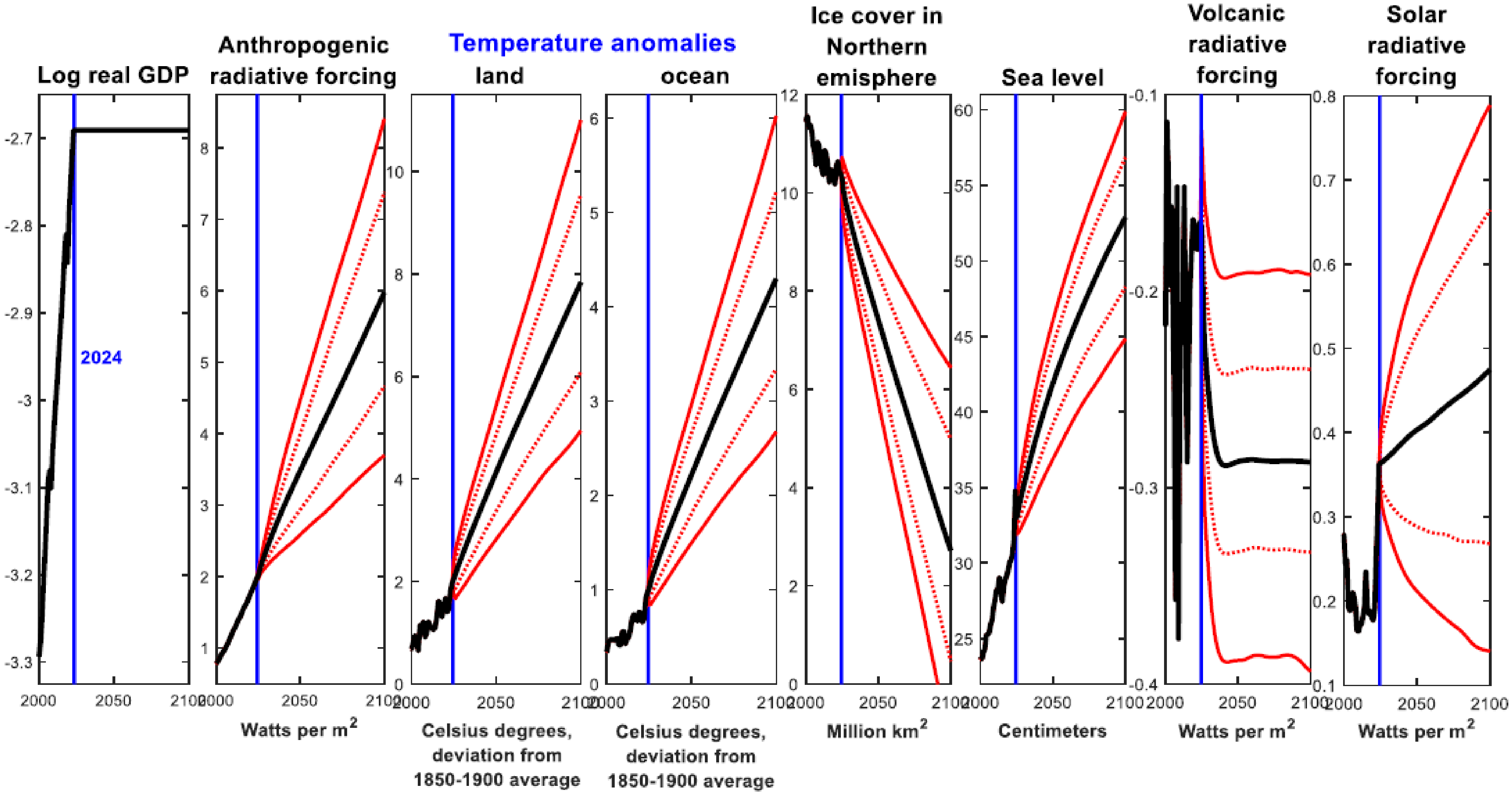

Figure 6 Forecasts keeping both real GDP and its anthropogenic radiative forcing intensity constant at their 2024 levels, (median, and 16-84 and 5-95 credible set)

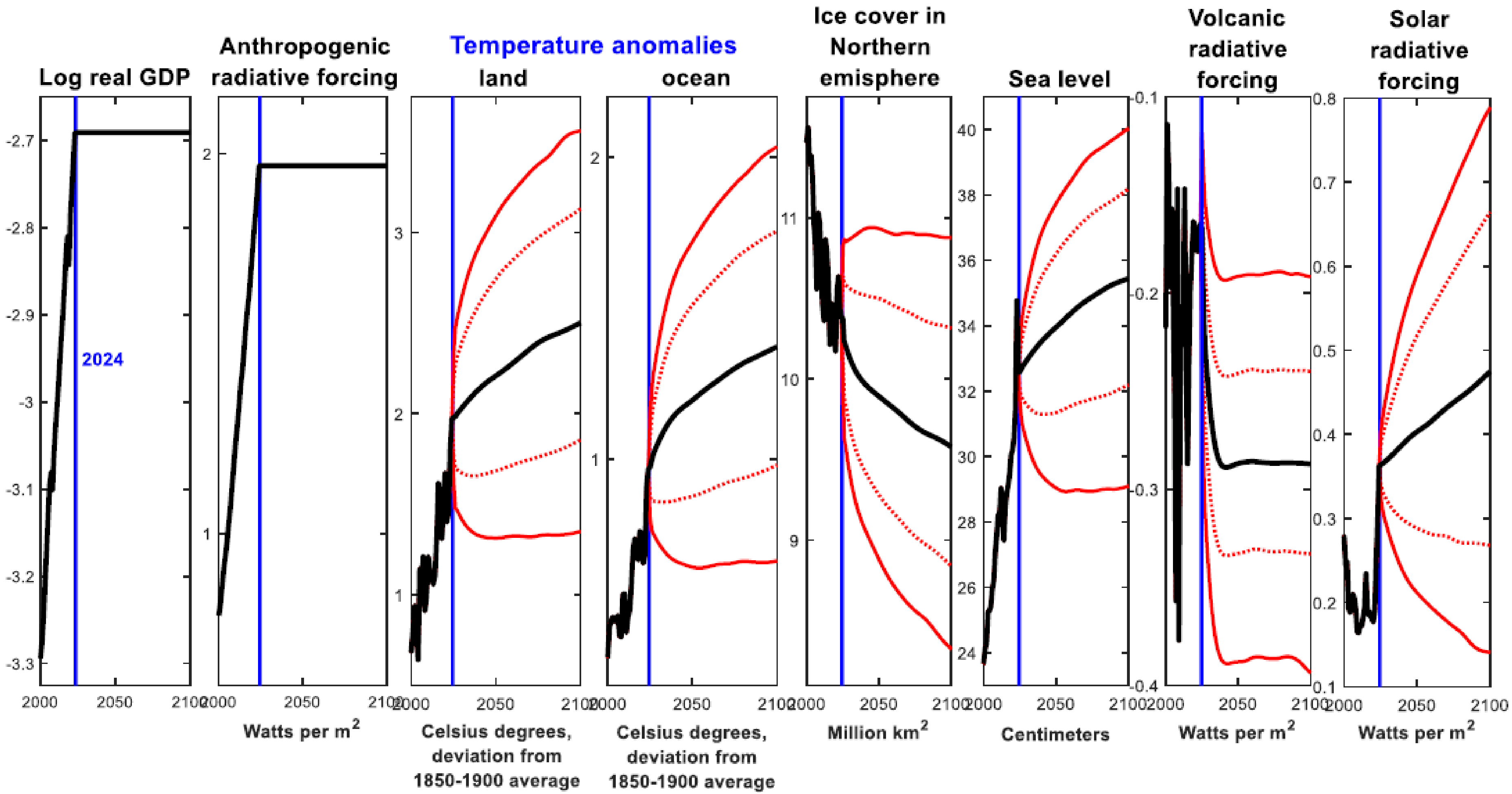

Figure 7 Forecasts keeping real GDP at its 2024 level, and assuming full decarbonization of the economy in 2025 (median, and 16-84 and 5-95 credible set)

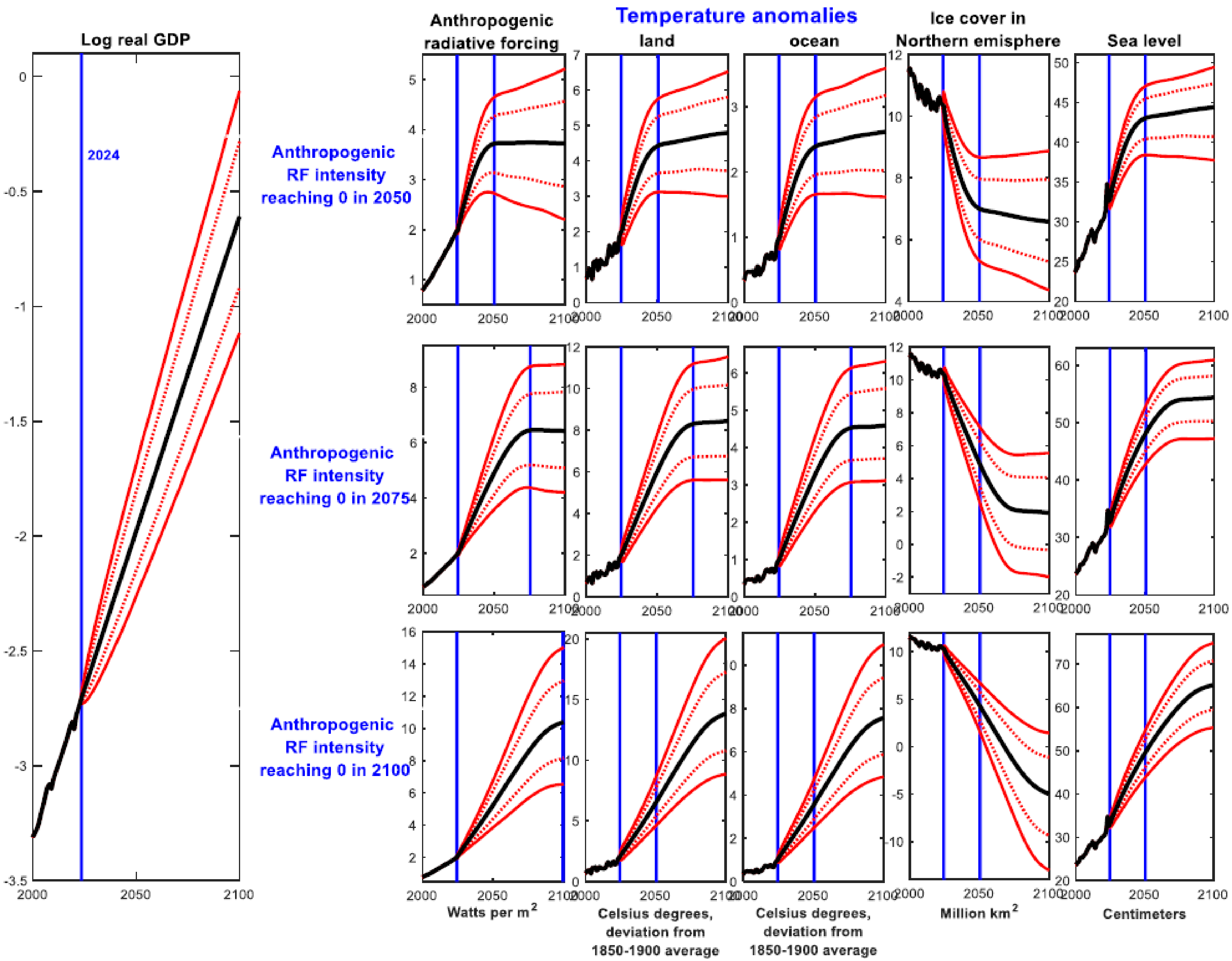

Figure 8 Forecasts with trend real GDP growth after 2024 set to the 2024 estimated value, and decreasing anthropogenic radiative forcing intensity of GDP (median, and 16-84 and 5-95 credible set)

by 2050, paints a grim picture, with the median forecast for the land temperature anomaly reaching a 4.9 Celsius degrees increase compared to pre-industrial times. Further, the upper bound of the 90 per cent-coverage credible set stretches to 6.5 degrees.

5.6 Removing carbon from the atmosphere

Clearly, limiting ourselves to full decarbonization by 2050 is *not enough*, which suggests that, after peaking sometime in the future, anthropogenic RF should be decreased via a massive programme of carbon removal from the atmosphere. The obvious question is: 'To what level should anthropogenic RF be brought back?' Figure 9 provides some evidence on this. The exercise is the same as in Figure 8, with the only difference that after peaking in 2050, anthropogenic RF is then brought back (in terms of its median projection) to the level of the early 1970s. Under this path for anthropogenic RF, the median projections for global land and ocean temperatures converge to about -0.5 and -0.3 degrees. The obvious reason for this undershooting compared to the 1.5 degrees target of the Paris accord is the large extent of uncertainty, with the upper limits of the 90%-coverage credible sets being equal to 2.1 and 1.1 degrees.

6 Estimating the Impact of Climate Change on GDP

Up until now I have assumed that GDP is unaffected by climate change. A sizeable literature has however estimated a negative impact of temperatures on output. The impact is especially large for the agriculture sector that is still sizeable, or even dominant, in developing countries, with temperature increases beyond certain thresholds being estimated to lead to sizeable falls in crop yields. By the same token, the well-documented increase in the frequency and intensity of storms and hurricanes has obvious economic costs, not only in terms of destruction of assets such as housing, but also in terms of disruption of production activity.

In this section I therefore modify the benchmark model I have been working with up until now in order to allow for a permanent impact of temperatures on world GDP. Whereas I leave the impact matrix of the structural shocks (A_0) unchanged, I modify the VAR matrices by allowing world GDP to be *directly* affected by lags of all variables except volcanic and solar RF, i.e. by lags of $\Delta RF_t^A - \beta_t GDP_t$, $JRF_t - \alpha_{\mathrm{L}} T_t^{\mathrm{L}}$, $JRF_t - \alpha_{\mathrm{O}} T_t^{\mathrm{O}}$, $T_t^* - \gamma_I I_t$, and $T_t^* - \gamma_S S_t$. So, to fix ideas, in the case of a single lag,

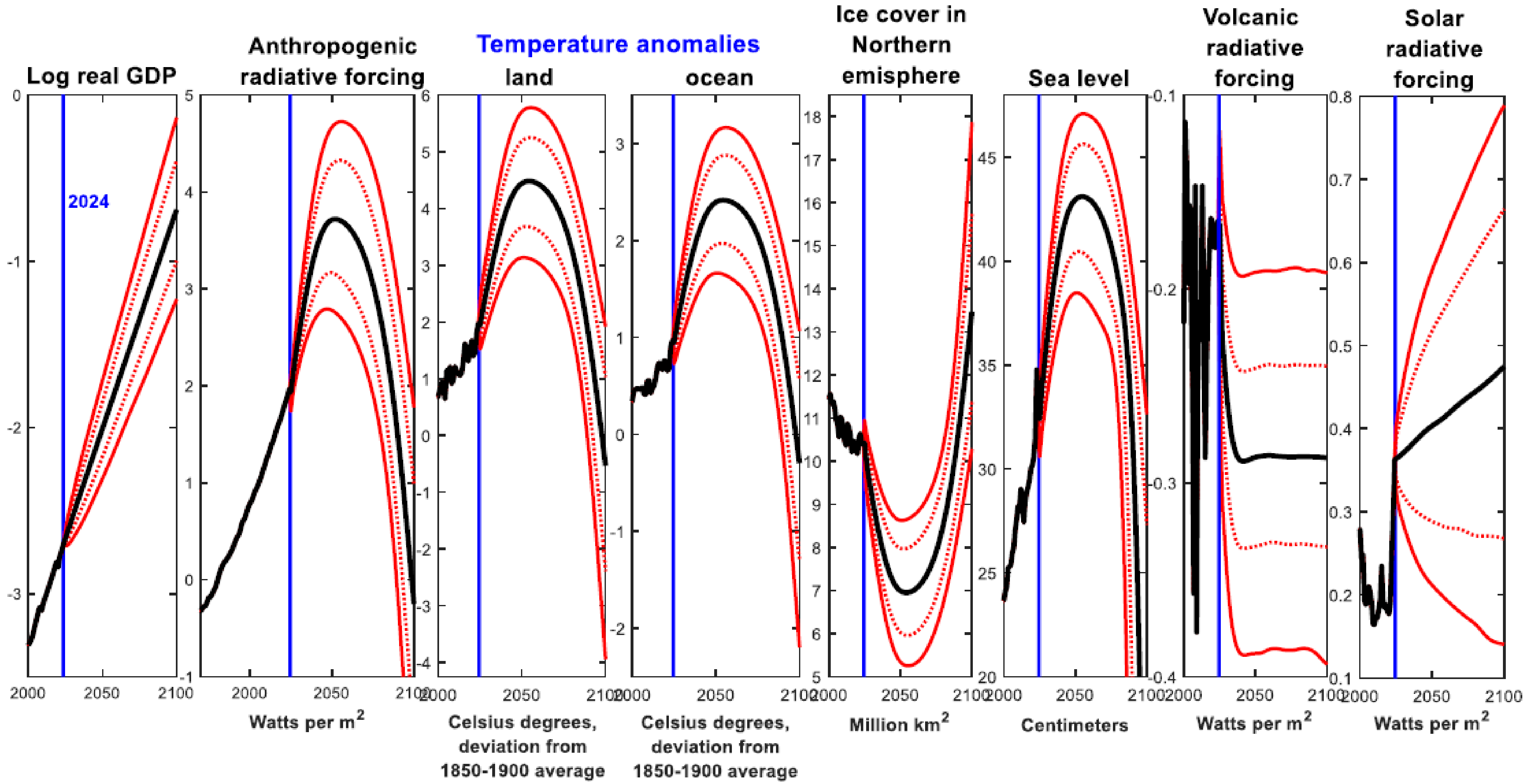

Figure 9 Forecasts with trend real GDP growth after 2024 set to the 2024 estimated value, and the anthropogenic radiative forcing intensity of GDP peaking at 2050 and then decreasing (median, and 16-84 and 5-95 credible set)

the matrix B_1 in (9) becomes

$$B_1 = \begin{bmatrix} x & x & x & x & x & x & & \\ x & x & x & x & x & x & & \\ x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x \\ & & & & & & x & \\ & & & & & & & x \end{bmatrix} \tag{10}$$

The rationale for excluding a direct impact of lags of volcanic and solar RF on GDP is that, as a matter both logic and climate science, their impacts should be expected to work via increases in temperatures.

I define the impact of climate change on GDP as the long-run (i.e., frequency-zero) impact on world real GDP of a shock ϵ_t^A that causes an increase in T_t^* by 1 Celsius degree. I compute this statistic, which I label as δ, for each draw from the posterior distribution. Finally, in estimation I impose a Beta(7.5, 7.5) prior for $\delta/100+50$. The corresponding prior for δ is shown in the second panel of Figure 10 in red. The prior has a mode of 0, and it has essentially zero probability mass for $|\delta|>45$. As the figure shows, it is quite uninformative, and it essentially allows for any value of δ between -40 and 40%. The black line in the second panel of Figure 10 is the posterior distribution of δ. It has a median of -16.2%, and a 16-84% credible set stretching between -26.7% and -5.9%. Further, 94.1% of the posterior distribution of δ is below zero, thus strongly suggesting that, in line with the previous literature, global warming has a negative impact on GDP.

7 Conclusions

In this paper I use Bayesian structural VARs with stochastic volatility to study the dynamics of global land and ocean temperatures, the sea level, and ice cover in the Northern emisphere since 1850, by exploiting (*i*) their long-run equilibrium relationship with climate change drivers (CCDs) and (*ii*) the relationship between world GDP and anthropogenic CCDs. Random variation in CCDs that causes a permanent increase in global temperatures by 1 Celsius degree is associated with a 16% permanent decrease in world GDP, with 94% of the posterior distribution below zero. Assuming that trend GDP growth will remain unchanged after 2024, and the world economy will fully decarbonize by 2050, land temperatures and the sea level are projected to increase by 4.9 degrees and 45 centimeters respectively compared to pre-industrial times. Further, uncertainty is substantial, pointing to significant upward risks. Because of this, bringing climate change under control will require a massive programme of carbon removal from the atmosphere, in order to bring anthropogenic CCDs back to the levels of the 1970s.

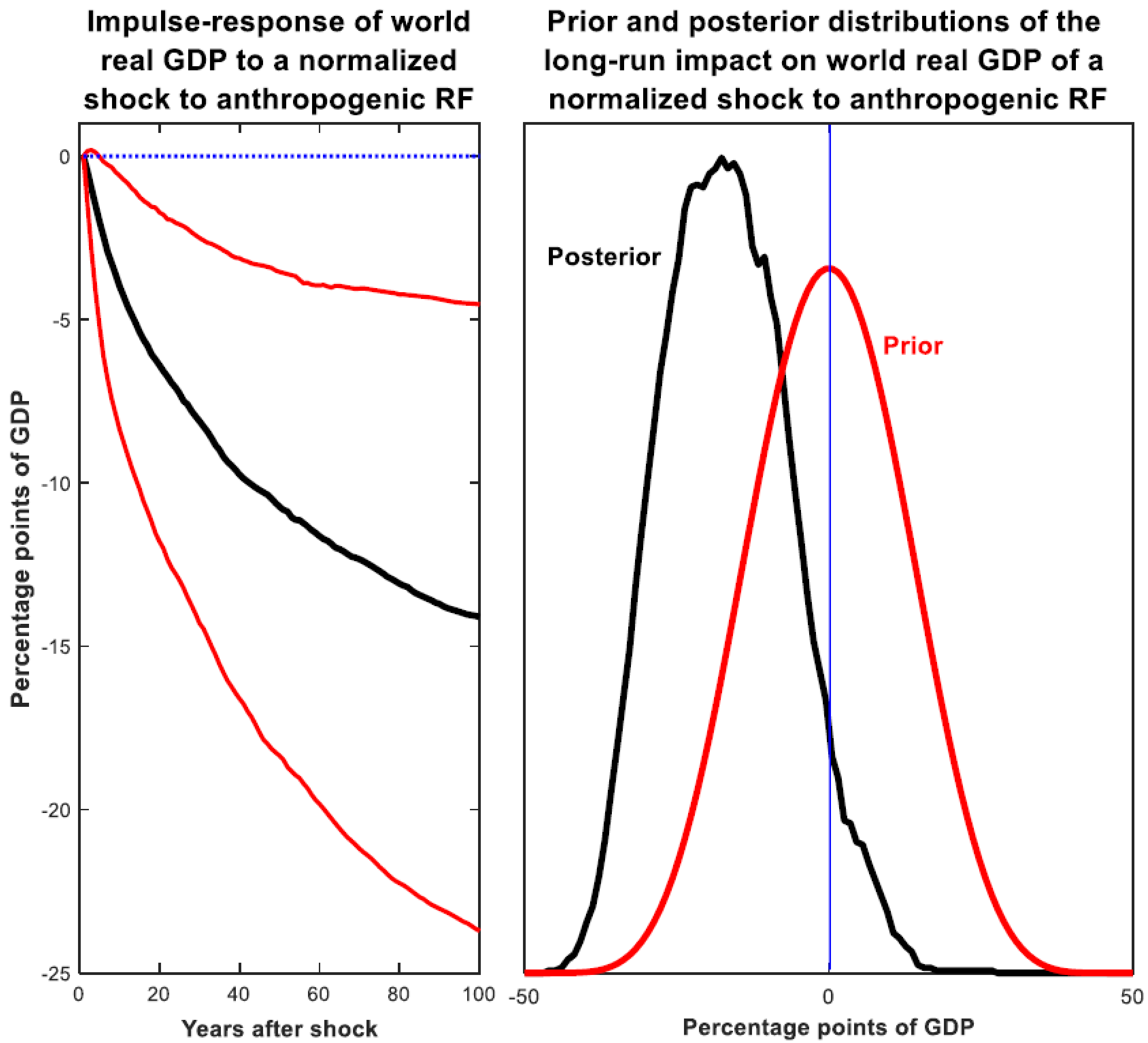

Figure 10 Impulse-response function of real GDP to random variation in radiative forcing leading to an increase in global temperatures by 1 Celsius degree (median and 16-84% credible set), and prior and posterior distributions of the long-run impact

8 References

An, S., and Schorfheide, F. (2007): “Bayesian Analysis of DSGE Models”, *Econometric Reviews*, 26, 113-172.

Anderson, T.W. (1951), “Estimating Linear Restrictions on Regression Coefficients for Multivariate Normal Distributions”, *Annals of Mathematical Statistics*, 22, 327-351.

Bauwens, L., and M. Lubrano (1996): “Identification Restrictions and Posterior Densities in Cointegrated Gaussian VAR Systems”, in Advances in Econometrics 11, Part B (JAI Press, Greenwich), 3-28

Beltrao, K. and P. Bloomfield (1987): “Determining the Bandwidth of a Kernel Spectrum Estimate”, *Journal of Time Series Analysis*, 8(1), 21-38.

Benati, L. (2007): “Drift and Breaks in Labor Productivity”, *Journal of Economic Dynamics and Control*, 31, 2847-2877.

Benati, L. (2008): “Investigating Inflation Persistence Across Monetary Regimes”, *Quarterly Journal of Economics*, 123(3), 1005-1060.

Bruns, S.B., Csereklyei, Z. and Stern, D.I. (2020): “A Multicointegration Model of Global Climate Change”, *Journal of Econometrics*, 214, 175-197.

Butler, J.H., and Montzka, S.A. (2018): “The NOAA Annual Greenhouse Gas Index (AGGI)”, NOAA Earth System Research Laboratory, Boulder, CO

Cavaliere, G., A. Rahbek, and A. M. R. Taylor (2012): “Bootstrap Determination of the Cointegration Rank in Vector Autoregressive Models”, *Econometrica*, 80(4), 1721-1740.

Church, J.A., and White, N.J. (2006): “A 20th century acceleration in global sea-level rise”, *Geophysical Research Letters*, 33, L01602.

Cochrane, J.H. (1988): “How Big Is the Random Walk in GNP?”, *Journal of Political Economy*, 96(5), 893-920

Coddington, O., Lean, J.L., Pilewskie, P., Snow, M., Lindholm, D. (2015): “A Solar Irradiance Climate Data Record”, *Bulletin of the American Meteorological Society*, p. 1265-1282.

Corana, A., Marchesi, M., Martini,C., and Ridella, S. (1987): “Minimizing Multimodal Functions of Continuous Variables with the Simulated Annealing Algorithm,” *ACM Transactions on Mathematical Software*, 13.

Dergiades, T., Kaufmann, R.K., Panagiotidis, T. (2016): “Long-Run Changes in Radiative Forcing and Surface Temperature: The Effect of Human Activity Over the Last Five Centuries”, *Journal of Environmental Economics and Management*, 76, 67-85.

Diebold, F.X. and Chen, C. (1996): “Testing Structural Stability with Endogenous Breakpoint: A Size Comparison of Analytic and Bootstrap Procedures”, *Journal of Econometrics*, 70(1), 221-241.

Elliot, G., T.J. Rothenberg and J.H. Stock (1996): “Efficient Tests for an Autoregressive Unit Root”, *Econometrica*, 64(4), 813-836.

Engle, R. F., and C. W. Granger (1987): "Cointegration and Error Correction: Representation, Estimation, and Testing", *Econometrica*, 55(2), 251-276.

Franke, J. and W. Hardle (1992): "On Bootstrapping Kernel Spectral Estimates", *Annals of Statistics*, 20(1), 121-145.

Gadea, M.D. and J. Gonzalo (2024), "Long-Term Climate forecasts", Universidad de Zaragoza and Universidad Carlos III, mimeo

Gelman, A., Carlin, J.B., Stern, H.S., and Rubin, D. (1995): *Bayesian Data Analysis*, New York, Chapman and Hall.

Geweke, J. (1992): "Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments", in J. M. Bernardo, J. Berger, A. P. Dawid and A. F. M. Smith (eds.), *Bayesian Statistics*, Oxford University Press, Oxford, pages 169-193.

Giannone, D., Lenza, M., and Primiceri, G. (2019): "Priors for the Long Run", *Journal of the American Statistical Association*, 114:526, pp. 565-580.

Goffe, W.L., Ferrier, G., and Rogers, J. (1994): "Global Optimization of Statistical Functions with Simulated Annealing", *Journal of Econometrics*, 60, 65-99.

Hamilton, J.D. (1986): "A Standard Error for the Estimated State Vector of a State-Space Model", *Journal of Econometrics*, 33(3), 387-397.

Kaufmann, R.K. and D.I. Stern (2002), "Cointegration Analysis of Hemispheric Temperature Relations", *Journal of Geophysical Research*, Vol. 107, N. D2, 4012, 10.1029/2000JD000174.

Kaufmann, R.K., H. Kauppi, and J.H. Stock (2006): "Emissions, Concentrations, and Temperature: A Time Series Analysis", *Climatic Change*, 77: 249-278.

Kaufmann, R.K., H. Kauppi, and J.H. Stock (2010): "Does Temperature Contain a Stochastic Trend? Evaluating Conflicting Statistical Results", *Climatic Change*, 101:395-405.

Kaufmann, R.K., H. Kauppi, M.L. Manna, and J.H. Stock (2011), "Reconciling Anthropogenic Climate Change with Observed Temperature 1998–2008, PNAS, July 19, 2011, Vol. 108, n. 29.

Kleibergen, F. and H.K. van Dijk (1994): "On the Shape of the Likelihood/Posterior in Cointegration Models", *Econometric Theory*, 10, 514-551.

Koop, G., Strachan, R., van Dijk, H., and Villani,M. (2006): "Bayesian Approaches to Cointegration", in K. Patterson and T. Mills, editors, *The Palgrave Handbook of Theoretical Econometrics*, Palgrave MacMillan

Koop, G., Léon-González, R., and Strachan, R.W. (2010): "Efficient Posterior Simulation for Cointegrated Models with Priors on the Cointegration Space", *Econometric Reviews*, 29(2), 224-242

Kopp, G. and G. Lawrence (2005): "The Total Irradiance Monitor (TIM): Instrument Design", *Solar Physics*, 230(1), 91-109.

Kopp, G, K. Heuerman, and G. Lawrence (2005): "The Total Irradiance Monitor (TIM): Instrument Calibration", *Solar Physics*, 230(1), 111-127.

Kopp, G., Krivova, N., Lean, J., and C.J. Wu (2016): "The Impact of the Revised Sunspot Record on Solar Irradiance Reconstructions", *Solar Physics*, p. 1-18.

Jacquier, E., Polson, N.G., and Rossi, P.E. (2007): "Bayesian Analysis of Stochastic Volatility Models", *Journal of Business & Economic Statistics*, Vol. 20, No. 1, Twentieth Anniversary Commemorative Issue (Jan., 2002), pp. 69-87.

Johansen, S. (1988), "Statistical Analysis of Cointegration Vectors", *Journal of Economic Dynamics and Control*, 12, 231-254.

Johansen, S. (1991), "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models", *Econometrica*, 69, 111-132.

Johansen, S. (1992), "A Representation of Vector Autoregressive Processes Integrated of Order 2", *Econometric Theory*, 8(2), 188-202.

Johansen, S. (1995), "A Statistical Analysis of Cointegration for I(2) Variables", *Econometric Theory*, 11(1), 25-59.

Johansen, S. (1997), "Likelihood Analysis of the I(2) Model", *Scandinavian Journal of Economics*, 24(4), 433-462.

Joshi, M.M., Gregory, J.M., Webb, M.J., Sexton, D.M.H., and Johns, T.J. (2008): "Mechanisms for the land/sea warming contrast exhibited by simulations of climate change", *Climate Dynamics*, Vol. 30, 455-465.

Juselius, K. (2006), *The Cointegrated VAR Model: Methodology and Applications*, Oxford University Press.

Justiniano, A. and Primiceri, G.E. (2008): "The Time-Varying Volatility of Macroeconomic Fluctuations", *American Economic Review*, 98:3, 604-641.

Lambert, F.H., Webb, M.J., and Joshi, M.M. (2011): "The Relationship between Land–Ocean Surface Temperature Contrast and Radiative Forcing", *Journal of Climate*, Vol. 24 (July), 3239-3256.

Liu, H., and Rodriguez, G. (2005): "Human Activities and Global Warming: A Cointegration Analysis", *Environmental Modelling & Software*, 20, 761-773.

Luetkepohl, H. (1991): *Introduction to Multiple Time Series Analysis*, 2nd edition. Springer-Verlag.

Mann, M. (2023): *Our Fragile Moment: How Lessons from the Earth's Past Can Help Us Survive the Climate Crisis*, Scribe, Melbourne and London.

Nyblom, J. (1989), "Testing for the Constancy of Parameters Over Time", *Journal of the American Statistical Association*, 84(405), 223-230.

Robertson, A., Overpeck, J., Rind, D., Mosley-Thompson, E., Zielinski, G., Lean, J., Koch, D., Penner, J., Tegen, I., and Healy, R. (2001): "Hypothesized Climate Forcing Time Series for the Last 500 Years", *Journal of Geophysical Resesearch Atmosphere*, Vol. 106(D14), p. 14, 783.

Schallock, J., Brühl, C., Bingen, C., Höpfner, M., Rieger, L., and Lelieveld, J. (2023): "Reconstructing volcanic radiative forcing since 1990, using a comprehensive emission inventory and spatially resolved sulfur injections from satellite data in a chemistry-climate model", *Atmospheric Chemistry and Physics*, 23, 1169-1207.

Shine, K.P.R.G., Derwent, D.J., Wuebbles, D.J., and Mocrette, J.J. (1991): "Radiative Forcing of Climate", in Houghton, J.T., Jenkins, G.J., and Ephramus, J.J., editors, *Climate Change: The IPCC Scientific Assessment*, Cambridge University Press, Cambridge, pp. 47-68.

Stern, D.I. and Kaufmann, R.K. (2000): "Detecting a Global Warming Signal in Hemispheric Temperature Series: A Structural Time Series Analysis", *Climatic Change*, 47, 411-438.

Stern, D.I. and Kaufmann, R.K. (2014): "Anthropogenic and Natural Causes of Climate Change", *Climate Change*, 122, 257-269.

Stock, J. and Watson, M. (1996): "Evidence of Structural Instability in Macroeconomic Time Series Relations", *Journal of Business and Economic Statistics*, 14(1), 11-30.

Stock, J. and Watson, M. (1998): "Median-Unbiased Estimation of Coefficient Variance in a Time-Varying Parameter Model", *Journal of the Americal Statistical Association*, 93(441), 349-358.

Strachan, R. and Inder, B. (2004): "Bayesian Analysis of the Error Correction Model", *Journal of Econometrics*, 123, 307-325.

Sutton, R.T., Dong, B., and Gregory, J.M. (2007): "Land/sea warming ratio in response to climate change: IPCC AR4 model results and comparison with observations", *Geophysical Research Letters*, Vol. 34, L02701.

Waggoner, D.F. and Zha, T. (1999): "Conditional Forecasts in Dynamic Multivariate Models", *Review of Economics and Statistics*, 81(4), 639-651.

Figures for Appendix

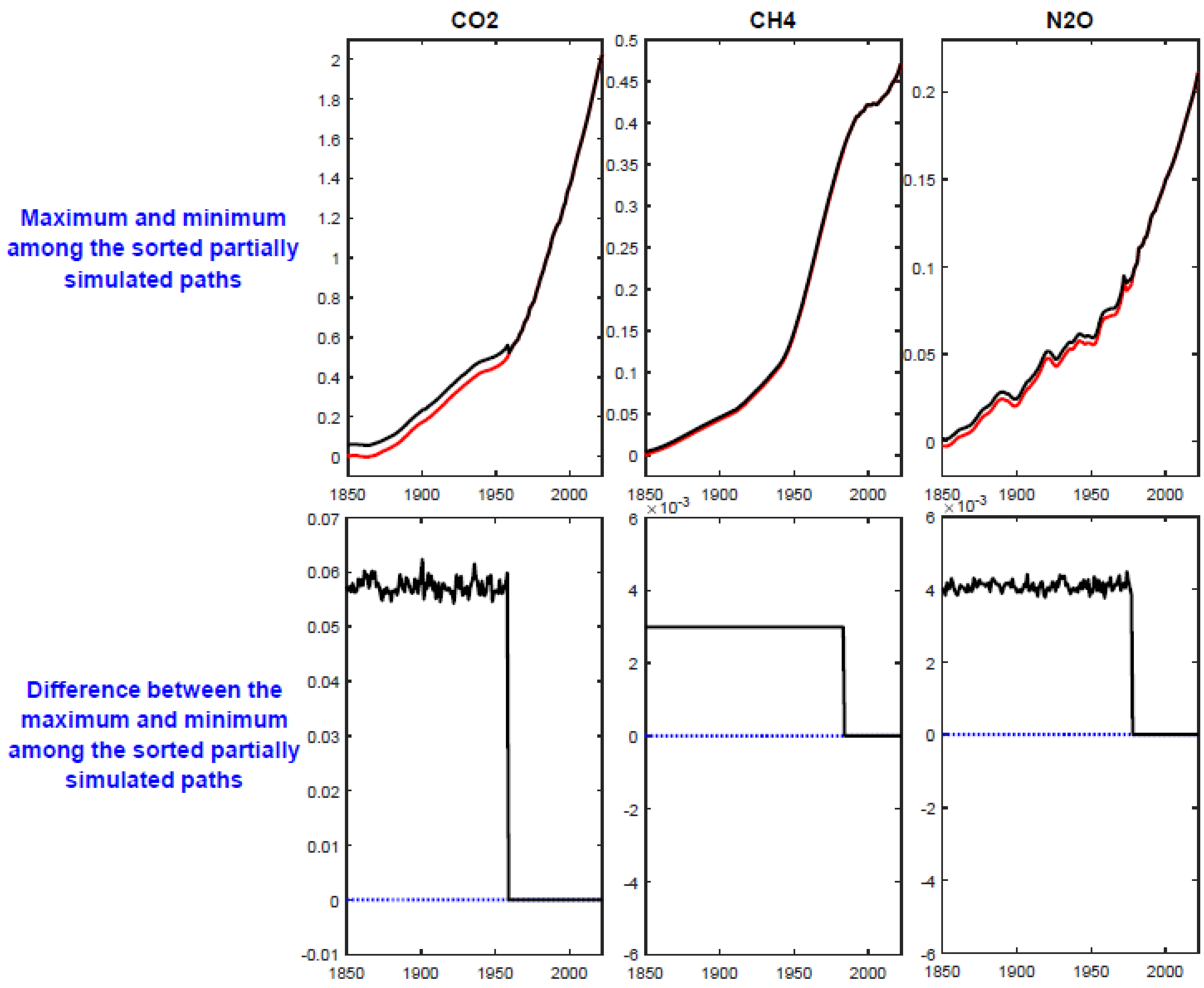

Figure A.1 Evidence on the close similarity between alternative partially simulated series for CO2, NH4, and N2O: maximum and minimum among the sorted partially simulated paths out of 100,000 simulations

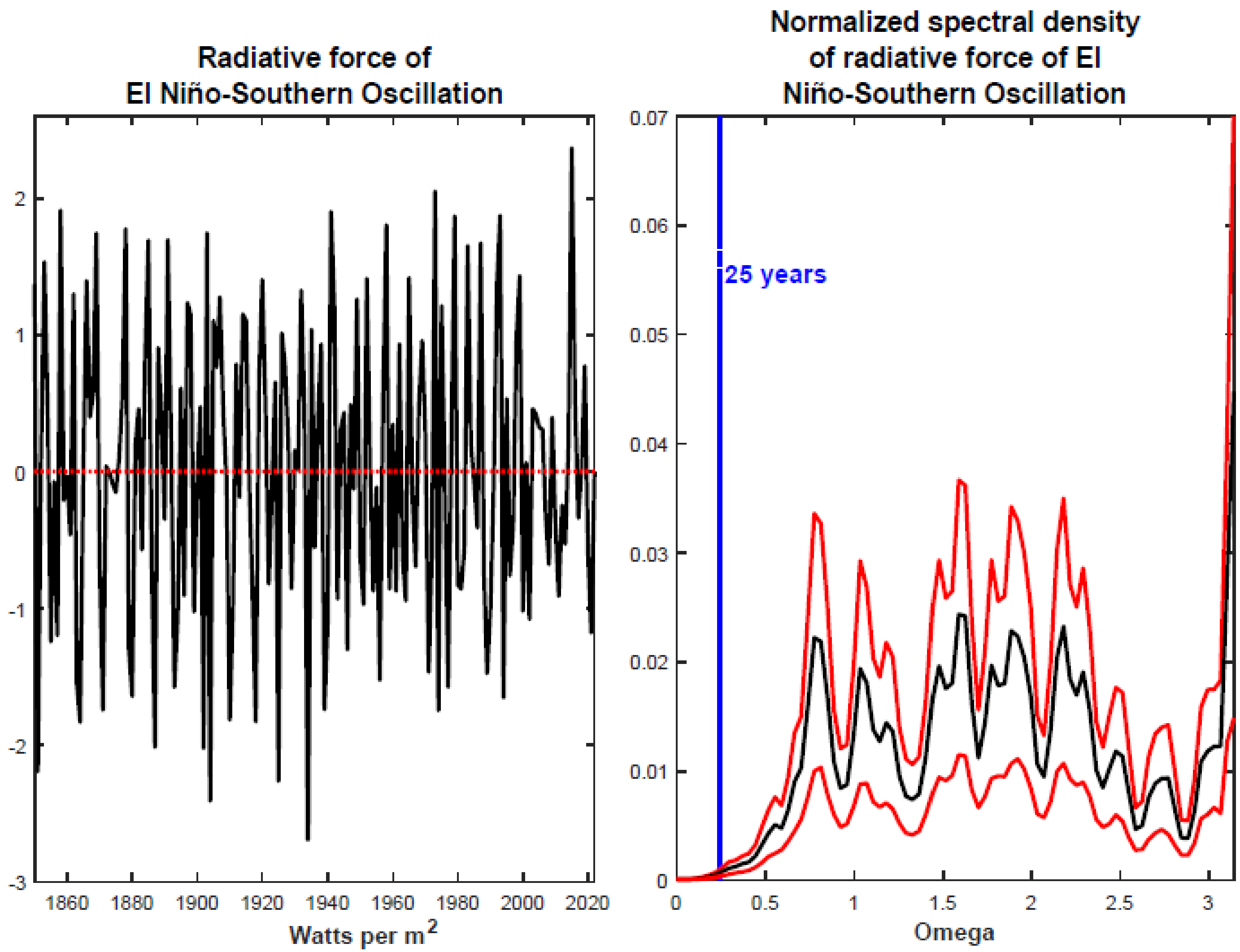

Figure A.2 Radiative force of El Niño-Southern Oscillation: raw series and normalized spectral density (with 90%-coverage bootstrapped confidence bands)