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Sceptic priors and climate consensus

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Abstract How much evidence would it take to convince sceptics that they are wrong about climate change? I explore this question within a Bayesian framework. I consider a group of stylised sceptics and examine how these individuals update their beliefs in the face of current and continuing climate change. I find that available evidence in the form of instrumental climate data tends to overwhelm all but the most extreme priors. Most sceptics form updated beliefs about climate sensitivity that correspond closely to estimates from the scientific literature. However, belief convergence is a non-linear function of prior strength. It thus becomes increasingly difficult to convince the remaining pool of sceptics. I discuss necessary conditions for consensus formation under Bayesian learning and show how apparent deviations from the Bayesian ideal still be accommodated within the same conceptual framework. I argue that a generalized Bayesian model thus provides a bridge between competing theories of climate scepticism as a social phenomenon.

Keywords climate sceptics · social cost of carbon · Bayesian econometrics ·

1 Introduction

Climate change has come to represent a defining policy issue of our age. Yet support for comprehensive climate policy at the global scale remains elusive. Many policy makers and citizens are openly sceptical about the human role

The data and source code for reproducing all of the results in this paper can be found at the companion GitHub repository: `https://github.com/grantmcdermott/sceptic-priors`

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in our changing climate, despite decades of accumulated research and an overwhelming scientific consensus ([1], [2], [3], [4], [5], [6], [7], [8]). What are we to make of this scepticism? And just how much evidence would it take to convince climate sceptics that they are wrong? In the present paper, I seek to answer these questions within a Bayesian framework that combines a range of sceptic beliefs (i.e. priors) with available climate data. My goal is to pin down plausible rates of convergence with the scientific consensus, by examining how different sceptics update their beliefs in the face of current and continuing climate change. In so doing, I hope to shed light on our current policy impasse and offer some remarks about the possibility for finding common ground in the future.

Many studies have explored the cultural and psychological factors underlying climate scepticism. These include [9], [10], [11], [12], [13], [14], [15], [16] — see [17] for a recent literature review. My present concern is less with the origins of scepticism than what it represents. Namely, a set of *beliefs* about the likely causes of global warming, which will in turn affect how new information about those causes is interpreted. A convenient way to model such beliefs is by defining scepticism in terms of climate sensitivity, i.e. the temperature response to a doubling of CO_2. Specifically, we can map sceptic beliefs directly on to subjective estimates of climate sensitivity, because they both describe the likely causes and probability distribution of future warming. The particular measure of climate sensitivity that I focus on here is the transient climate response (TCR). Formally, TCR describes the warming at the time of CO_2 doubling — i.e. after 70 years — in a 1% per year increasing CO_2 experiment [18]. For the purposes of this paper, however, it will simply be thought of as the contemporaneous change in global temperature that results from a steady doubling of atmospheric CO_2.

According to the the Intergovernmental Panel on Climate Change [18], TCR is "likely" to be somewhere in the range of 1.0–2.5 °C. This corresponds roughly to a 66–100% probability interval in IPCC terminology. The IPCC further emphasizes the inherently Bayesian nature of climate sensitivity estimates, going so far as to state:

> *[T]he probabilistic estimates available in the literature for climate system parameters, such as ECS [i.e. equilibrium climate sensitivity] and TCR have all been based, implicitly or explicitly, on adopting a Bayesian approach and therefore, even if it is not explicitly stated, involve using some kind of prior information.* [18, p. 922]

To understand why classical (i.e. frequentist) methods are ill-suited for the task of producing credible estimates of climate sensitivity, recall that frequentism interprets probability as the limiting frequency in a large number of repeated draws. Such a narrow definition holds little relevance to the question of climate sensitivity, for which there exists but one unique value. There is no population of "sensitivities" to draw samples from. I also adopt a Bayesian framework to determine climate sensitivity and its concomitant policy implications. However, my approach differs from the previous literature along several dimensions.

The most obvious point of departure is the fact that I deliberately focus on the beliefs of sceptics. Priors for determining climate sensitivity are usually based on paleo data, the judgments of scientific experts, or noninformative methods. Such approaches may possess obvious scientific merit for establishing a best estimate of climate sensitivity. Yet, they are of limited relevance for understanding people's motivations and voting behaviour when it comes to actual climate policy. My approach is to take sceptics at their word and work through to the conclusions of their stated priors. In other words, my goal is to recover posterior probabilities about the rate and causes of climate change that are logically consistent with the initial beliefs of these sceptics.

Contrarian climate beliefs have also been largely ignored in the economic policy literature to date. The handful of studies that do consider policy options from the sceptic perspective have tended to emphasise edge scenarios like climate catastrophe and irreversibility. For example, [19] introduces an IAM of heterogeneous agents that incorporates various degrees of climate scepticism. She shows that a world comprised only of sceptical policy makers will make sufficient investments in mitigation measures to avoid catastrophic outcomes. The key mechanism is a dominant subset of "weak" sceptics who are sufficiently concerned by anthropogenic climate change that they reduce their emissions accordingly. [19] does not allow for learning in her simulations.[1] However, theoretical work by [21] show that climate sceptics actually have an incentive to reduce emissions, since it will facilitate learning about the true causes of climate change. While it is possible for an increase in emissions to yield similar learning effects, the irreversibility of climate change renders this an inferior strategy. From a methodological perspective, the present paper differs from these earlier studies by combining Bayesian learning with an empirical framework.[2]

Unlike the existing numerical and game-theoretic approaches, described above, I am not attempting to prescribe an optimal emissions strategy or learning paths for climate sceptics under future uncertainty. Rather, my goal is to establish some ground rules for thinking about climate policy today, given the information that is already available to us.

Another distinguishing feature of this paper is that the results are derived via conceptually straightforward time-series regression analysis. While climate scientists have typically relied on complex computer models to simulate TCR,

[1] It should be said that there *is* an important literature on Bayesian learning in IAMs that originates with [20]. But I am not aware of any study that attempts to integrate learning by climate sceptics into an IAM.

[2] In terms of tangentially related empirical work, [22] shows that spatial heterogeneity in local climate change effects and temperatures can partially explain persistent scepticism in different regions of the United States. [23] does not deal with sceptics *per se*, but characterises learning about climate as a (potentially) Bayesian process where individuals make inferences based on local weather shocks. This builds off of earlier work by [24], who finds that longer spells of abnormal local weather patterns are consistent with Bayesian updating about climate beliefs.

a growing body of research is aimed at understanding the link between human activities and climate change through the purview of time-series econometrics. Much of this literature has concerned itself with the apparent non-stationarity of climate data over time. The present paper takes as its foundation recent research ([25], [26], [27], [28]), which argues convincingly that global surface temperatures and anthropogenic forcings are best described as trend-stationary processes, incorporating common structural breaks.[3] The upshot is to permit the use of level terms within an ordinary least squares (OLS) regression framework. Such matters notwithstanding, virtually all econometric studies of climate change attribution to date have been carried out in the frequentist paradigm. They do not consider the influence of priors, nor are they able to yield the probabilistic estimates that are characteristic of Bayesian analysis. A noteworthy and early exception is that of [32], who are motivated to adopt a Bayesian approach because of multicollinearity in their anthropogenic emissions data. Such multicollinearity does not plague newer datasets, since these are defined in common units as will be discussed in Section 4. Further, [32] do not consider the influence of overtly contrarian priors as a basis for affecting policy.

2 Econometric approach

2.1 Bayesian regression overview

The Bayesian regression framework is less familiar to many researchers than the frequentist paradigm that is commonly taught in universities. For this reason, I provide a brief overview of the key principles of the Bayesian method and highlight some important distinctions versus the frequentist approach.

A Bayesian regression model uses the logical structure of Bayes' theorem to estimate probable values of a set of parameters θ, given data X:

$$p(\theta|X) = \frac{p(X|\theta)p(\theta)}{p(X)}. \tag{1}$$

Here, $p(\theta|X)$ is known as the *posterior* and serves as the fundamental criterion of interest in the Bayesian framework. The posterior asks, "What are the probable values of our parameters, given the observed data?" This stands in direct contrast to the first term in the right-hand numerator, $p(X|\theta)$, which is the familiar *likelihood function* from frequentist statistics. The likelihood essentially reverses the question posed by the posterior and instead asks, "How likely we are to observe some data for a given set of parameters (e.g. based on an assumption about the data generating process)?" The second term in the numerator is the *prior*, $p(\theta)$. While the prior can take on any distributional

[3] Another group of researchers beginning with [29], has argued that the instrumental temperature record contains a stochastic trend that is imparted by, and therefore cointegrates with, the time-series data of radiative forcings. The reader is referred to [30] and [31] for a helpful overviews of this debate.

form, it should in principle encapsulate our knowledge about the parameters before we have observed the data. Insofar as we are interested in learning about θ, it is common practice to ignore the term in the denominator, $p(X)$. This is simply the marginal probability of the data and can be thought of as a normalisation constant, which helps to ensure that the posterior is a proper probability distribution (i.e. integrates to one) and can be calculated *ad hoc* if needed. For this reason, eq.(1) is typically re-written as

$$p(\theta|X) \propto p(X|\theta)p(\theta). \tag{2}$$

Equation (2) embodies the mantra of Bayesian statistics: "The posterior is proportional to the likelihood times the prior." Solving for the posterior typically involves the combination of various integrals, which cannot be calculated analytically.[4] Fortunately, we can simulate the posterior density computationally using Markov Chain Monte Carlo (MCMC) routines. This can be done for virtually any combination of prior and likelihood function. Obtaining a valid posterior is then simply a matter of: (i) choosing a prior distribution for our regression parameters, i.e. regression coefficients and variances; and (ii) specifying a likelihood function to fit the data. For ease of exposition — how we map parameter values to beliefs about TCR will be determined by the specification of the regression model — I begin with the likelihood function.

2.2 Likelihood function

The likelihood function is governed by the choice of empirical model. Following [33] and [26], I model global temperatures using the regression equation

$$GMST_t = \alpha_0 + \beta_1 RF_t + \gamma_2 VOLC_t + \delta_3 SOI_t + \eta_4 AMO_t + \epsilon_t, \tag{3}$$

where $\epsilon_t = \phi\epsilon_{t-1} + \nu_t$ is a first-order autoregressive, or AR(1), error process.

Here, $GMST$ is the global mean surface temperature anomaly relative to the pre-industrial period (defined as the 1871–1900 average); RF is total radiative forcing due to both anthropogenic and natural factors (excluding volcanic eruptions); $VOLC$ is the radiative forcing due to volcanic stratospheric aerosols; and SOI and AMO are scaled indices of these respective climatic phenomena. The subscript t denotes time. Specifying that the error term ϵ follows an AR(1) process allows us to account for dynamic elements such as potential autocorrelation.

Two points merit further discussion before continuing. First, nothing much hinges on the use of OLS for estimating TCR. For example, the β_1 coefficient above is equivalent to the "climate resistance" constant (ρ) described in [34]; a point I shall return to later. OLS simply provides a convenient method for

[4] A famous exception is that of conjugate priors, which belong to the same distribution family as the resulting posterior. However, this places strong restrictions on the questions that can asked of the data.

combining data and priors in a consistent Bayesian framework. Other methods could in principle be used to derive the same results. Second, the use of a composite *RF* variable that combines both anthropogenic and natural forcings may, at first blush, seem an odd choice. After all, the goal of this paper is to separate out and interrogate scepticism specifically about the human role in climate change. However, recall that the underlying forcings in my dataset are all expressed in terms of a common unit (i.e. Wm^{-2}). This circumvents the multicollinearity problems that would arise from estimating an econometric model on forcings that have been separated out.[5] Econometric issues aside, the use of a common forcing unit ensures that I don't run the risk of estimating different coefficients, which would imply an inconsistent response of the climate system to identical forcings. The use of a composite forcing series is thus a necessary step to ensure that the model remains physically consistent.[6] Nonetheless, I show in an alternate specification later in the paper that relaxing this constraint leads to near identical conclusions as the physically correct specification. I also show that the core results do not hinge on the imposition of a common efficacy among different forcing agents.

Returning to my primary regression model, eq. (3) implies a likelihood function that is multivariate normal

$$p(GMST|\boldsymbol{\beta},\sigma^2) = \frac{1}{(2\pi\sigma^2)^{T/2}} \exp\left[-\frac{(GMST-\mathbf{X}\boldsymbol{\beta})'(GMST-\mathbf{X}\boldsymbol{\beta})}{2\sigma^2}\right], \quad (4)$$

where $\mathbf{X}$ is the design matrix of explanatory variables; $\boldsymbol{\beta}$ is the coefficient vector; $\sigma^2 = \text{Var}(\epsilon)$ is the variance of the error term; and $T = 140$ is the number of years in the collated, historical dataset. Eq. (4) can also be written more simply as $GMST|\boldsymbol{\beta},\sigma^2 \sim \mathcal{N}_T(\mathbf{X}\boldsymbol{\beta},\sigma^2\mathbf{I})$.

An important feature of eqs. (3) and (4) is that they define how we should map probabilities about the regression parameters to beliefs about climate sensitivity. Recall that TCR describes the contemporaneous change in temperature that will accompany a steady doubling of atmospheric CO_2 concentrations. It follows that

$$\text{TCR} = \beta_1 * F_{2\times} \ , \quad (5)$$

where β_1 is the regression coefficient describing how responsive global temperatures are to a change in total radiative forcing, and $F_{2\times}$ is the change in forcing that results from a doubling of CO_2. For the latter, I use the IPCC's best estimate of $F_{2\times} = 3.71$ Wm^{-2} and further assume an additional $\pm 10\%$

[5] Anthropogenic forcings such as CO_2, CH_4, and N_2O all follow very similar trends over time. Any empirical model that does not constrain these forcings in some way will therefore struggle to correctly attribute warming between them.

[6] Volcanic aerosols are an exception because they impart only a transitory level of forcing. This explains why *VOLC* may be included as a separate component in the regression equation [26].

variation to account for uncertainties over spatial heterogeneity and cloud formation ([35] and [36]).[7] The key point is that assigning a distribution over the parameter β_1 will necessarily imply a distribution for TCR, and vice versa. We therefore have a direct means of linking prior and posterior probabilities of the regression parameters to beliefs about TCR. It also means that the primary goal of the regression analysis will be to determine probable values of β_1. The rest of the parameters will take a backseat in the analysis that follows, acting largely as controls.

Eq. (5) contains an implicit assumption that will have bearing on the external validity of my results — specifically, the extent to which they can be extrapolated to different future climate scenarios. Recall, as stated earlier, that β_1 is equivalent to the "climate resistance" parameter (ρ) defined in [34] as the constant sum of the ocean heat uptake efficiency and the climate feedback parameter. The importance of this equivalence is that it underscores the role of oceanic thermal dynamics in assuming a linear scaling between the different climate components of my regression model. While the linear relationship holds for scenarios where radiative forcing increases at steady rates — as was true for the historical period under consideration — it cannot be expected to do so in scenarios that overturn it. In such cases, ocean heat uptake would need to be modeled separately to account for inertia in the climate system and its resultant impact on GMST (*ibid.*). All of which is to say that I will limit my analysis to the historical period, as well as future climate scenarios that are characterised by steady increases in radiative forcing.

3 Priors

Climate scepticism is a matter of degree. I account for this fact by defining a simple typology of sceptics as per Table 1. Summarizing, I distinguish between two basic sceptic archetypes based on their best guess for TCR. *Lukewarmers* believe that TCR lies around 1 °C — i.e. the lower bound of the IPCC likely range (c.f. [41]) — while *deniers* believe that TCR is likely zero. I further distinguish these individuals based on how certain they are about their best guess. A person with *moderate* convictions believes that the true value of TCR lies within a 1 °C uncertainty interval of their prior mean (95% probability), while that interval falls to just 0.25 °C for someone with *strong* convictions. Altogether this yields a spectrum of sceptic priors that ranges from moderate lukewarmers to strong deniers. Importantly, each sceptic can all be represented mathematically by a prior distribution on TCR. I assume normal distributions for simplicity, where the mean represents an individual's best guess and the variance their uncertainty.[8] Following eq. (5), obtaining priors over β_1 is a sim-

[7] It is worth noting that a number of studies which provide climate sensitivity estimates via time-series methods — e.g. [37], [38], [33] — do so under the assumption that $F_{2\times} = 4.37$ Wm^{-2}. This outdated figure appears to be based on early calculations by [39]. The climate sensitivity estimates of these studies may consequently be regarded as inflated.

[8] The choice of normally-distributed priors should have little bearing on the generality of the results. An exception might occur if I assumed a bounded prior, like a triangular or

Table 1 Sceptic priors

Type	TCR (°C)	Implied β_1
Moderate lukewarmer	$\mathcal{N}(1,\ 0.25^2)$	$\mathcal{N}(0.27,\ 0.0674^2)$
Strong lukewarmer	$\mathcal{N}(1,\ 0.065^2)$	$\mathcal{N}(0.27,\ 0.0175^2)$
Moderate denier	$\mathcal{N}(0,\ 0.25^2)$	$\mathcal{N}(0,\ 0.0674^2)$
Strong denier	$\mathcal{N}(0,\ 0.065^2)$	$\mathcal{N}(0,\ 0.0175^2)$
Noninformative	–	$\mathcal{N}(0,\ 1.214^2)$

Notes: Subjective priors types are defined according to the mean (Lukewarmer vs Denier) and variance (moderate vs strong) parameters of normal distributions over TCR. The implied priors for β_1 are obtained using the simple formula described in eq. (5), i.e. $\beta_1 = \text{TCR}/3.71$. The noninformative prior presented at the bottom of the table is weakly data-dependent (i.e. depends on the scale of the data) and is obtained using the default calculation proposed by [40], $\beta_1 \sim \mathcal{N}(0,\ 2.5 \cdot \text{sd}(GMST)/\text{sd}(RF))$. See text for details.

ple matter of dividing the respective TCR distributions by $F_{2\times} = 3.71\ \text{Wm}^{-2}$. These are the parameters that actually enter the Bayesian regression model and are also shown in Table 1.

In addition to the subjective priors of our stylised sceptics, a useful reference case for the analysis is provided by a set of so-called *noninformative* priors. Loosely speaking, noninformative priors are vague and should not privilege particular parameter values over others. In practice, however, applied Bayesian researchers are advised to use noninformative priors that are weakly data-dependent ([43]). For example, priors should be scaled to reflect feasible magnitudes of the underlying data. If the data are observed in the order of millimeters, then the prior should not allocate plausible weight to values in the order of kilometers, etc. This modest form of regularisation not only helps to ensure computational stability, but also avoids some of the theoretical pathologies associated with uniform priors (c.f. [44]). I therefore use a set of reference priors that have been scaled to reflect this limited data dependence. Specifically, given generic dependent variable y and independent variable x, I define a noninformative prior for the associated regression coefficient $\beta_x \sim \mathcal{N}(0,\ 2.5\frac{s_y}{s_x})$, where $s_x = \text{sd}(x)$.[9] In other words, my noninformative priors take the form of normal distributions with wide variances. For my default regression specification this equates to a prior on the key radiative forcing coefficient of $\beta_1 \sim \mathcal{N}(0,\ 1.214^2)$.

Note that my group of sceptics only hold subjective priors over TCR (and thus β_1). Noninformative priors are always assumed for the remaining parameters in the regression equation. Similarly, I acknowledge that these sceptics are,

uniform distribution. Because these bounded distributions assign zero weight to outcomes beyond a specific interval, no amount of data can shift the posterior beyond that interval. This idea, that a Bayesian posterior can converge on a particular outcome only if the prior allocates some (infinitesimal) weight to it, is known colloquially as *Cromwell's rule* ([42]).

[9] This is the default prior suggested by [40], which they refer to as "weakly informative".

Table 2 Data sources

Variable	Key	Description	Period
GMST	HadCRUT4[a]	Global mean surface temperature. Primary series. Compiled by the UK Met Office and the Climatic Research Unit at the University of East Anglia.	1850–2019
	CW14[b]	Secondary series. Compiled by [45]. Corrects for coverage bias in HadCRUT4.	1850–2019
	GISTEMP[c]	Secondary series. Compiled by the NASA Goddard Institute for Space Studies.	1880–2015
RF	RCP[d]	Total radiative forcing due to anthropogenic and natural factors (excluding volcanic aerosols). Compiled by [46]. Historical data until 2005, simulated scenarios thereafter.	1765–2300
	DF18[e]	Ensemble of 1,000 radiative forcing estimates compiled by [47]. Used for sensitivity analysis.	1750–2017
VOLC	RCP[d]	Radiative forcing due to volcanic stratospheric aerosols. Compiled by [46].	1750–2005
AMO	NOAA[f]	Atlantic Multidecadal Oscillation.	1856–2019
SOI	NCAR[g]	Southern Oscillation Index.	1866–2019

Notes: The compiled dataset, as well as the code needed to reconstruct from source, are available at `https://github.com/grantmcdermott/sceptic-priors`. Sources are listed below.

[a] `http://www.metoffice.gov.uk/hadobs/hadcrut4/data/current/download.html`
[b] `http://www-users.york.ac.uk/~kdc3/papers/coverage2013/series.html`
[c] `http://data.giss.nasa.gov/gistemp`
[d] `http://www.pik-potsdam.de/~mmalte/rcps`
[e] `https://doi.org/10.5281/zenodo.1323162`, (original) `https://github.com/hausfath/OldModels` (accessed)
[f] `http://www.esrl.noaa.gov/psd/data/timeseries/AMO`
[g] `http://www.cgd.ucar.edu/cas/catalog/climind/soi.html`

of course, highly stylised caricatures. Their priors are simply taken as given. I am not concerned with where these priors come from and why they are of a particular strength. However, such abstractions are ultimately unimportant given the objectives of this study. My goal is to explore how climate sceptics would respond to evidence for climate change, provided that they update their beliefs rationally. Moreover, it gives a sense of just how strong someone's prior beliefs need to be, so as to preclude the acceptance of any policy interventions.

4 Data

The various data sources for this paper are summarised in Table 2. Global mean surface temperature data (1850–2017) are taken from the HadCRUT4 dataset, jointly compiled by the UK Met Office and the Climatic Research Unit at the University of East Anglia. Two alternate global temperature reconstructions — one provided by [45] and the other by the NASA Goddard Institute for Space Studies (GISTEMP) — are used as a check against coverage issues and other uncertainties. Radiative forcing data, covering both historic estimates (1765–2005) and future scenarios (2006-2300), are taken from the Representative Concentration Pathway (RCP) database, hosted by the Potsdam Institute for Climate Impact Research. These data include anthropogenic sources of radiative forcing like industrial greenhouse gas emissions, as well as natural sources like solar irradiance and volcanic eruptions. As a part of the sensitivity analyses, I use an ensemble of 1,000 forcing estimates to capture measurement uncertainty about radiative forcing data. This ensemble originates with [47], although I use a recapitulated version provided by [48] for ease of access. Data for two major oceanic-atmospheric phenomena, the Atlantic Multidecadal Oscillation (AMO, 1856–2017) and the Southern Oscillation Index (SOI, 1866–2017), are taken from the U.S. National Oceanic and Atmospheric Administration (NOAA) and National Center for Atmospheric Research (NCAR). Summarising the common historic dataset for which data are available across all series, we have 140 annual observations running over 1866–2005. RCP scenarios until 2100 will also be considered for making future predictions later in the paper.

5 Results

The analysis for this project was primarily conducted in `R` ([49], version 4.0.2), with the Bayesian computation being passed on to the `Stan` programming language ([50]). All of the code and data needed to reproduce the results can be found at the companion GitHub repository.[10]

5.1 Regression results and updated TCR beliefs

The posterior regression results for the various prior types are presented in Table 3. Each column contains the results from running the Bayesian regression eq. (3) over the full historical data set (1866–2005), using a particular set of priors. Beginning with the noninformative case in the first column, all of the regression coefficients are credibly different from zero and of the anticipated sign. For example, GMST is negatively correlated with SOI. This is to be expected since the El Niño phenomenon is defined by SOI moving into its negative phase. The posterior coefficient density on our main parameter of interest, total radiative forcing (RF), shows that global temperature will rise by an average of 0.426 °C for every Wm^{-2} increase. Of greater interest, however, is the fact that the posterior estimates yielded by the group of sceptic priors are very similar to this noninformative case. With the exception of the Strong Denier, there is a clear tendency to congregate towards the noninformative parameter values.

Of course, the exact values of the regression parameters are themselves of somewhat limited interest. Rather, their primary usefulness is to enable the

[10] `https://github.com/grantmcdermott/sceptic-priors`.

Table 3 Regression results and implied TCR

		Lukewarmer		Denier	
	Noninformative	Moderate	Strong	Moderate	Strong
RF	0.426	0.417	0.345	0.402	0.076
	(0.395, 0.455)	(0.387, 0.448)	(0.317, 0.373)	(0.371, 0.433)	(0.040, 0.112)
VOLC	0.048	0.048	0.046	0.047	0.034
	(-0.002, 0.098)	(-0.000, 0.097)	(-0.013, 0.102)	(-0.006, 0.097)	(-0.080, 0.148)
SOI	-0.024	-0.024	-0.025	-0.024	-0.025
	(-0.035, -0.012)	(-0.035, -0.013)	(-0.038, -0.014)	(-0.036, -0.013)	(-0.044, -0.006)
AMO	0.470	0.468	0.460	0.468	0.448
	(0.393, 0.548)	(0.386, 0.547)	(0.367, 0.552)	(0.386, 0.549)	(0.289, 0.614)
AR(1)	0.320	0.321	0.378	0.326	0.648
	(0.181, 0.444)	(0.187, 0.446)	(0.245, 0.503)	(0.194, 0.454)	(0.549, 0.733)
TCR	1.6	1.5	1.3	1.5	0.3
	(1.4, 1.8)	(1.4, 1.7)	(1.1, 1.4)	(1.3, 1.7)	(0.1, 0.4)

Notes: Results from running the Bayesian regression eq. (3). The table lists the posterior parameter means, with 95% Bayesian credible intervals in parentheses. Models are distinguished by the set of priors that were used during the Bayesian estimation. For the first model in column (1), noninformative priors were specified over all regression parameters. For the remaining models in columns (2)–(5), subjective priors were specified over the total radiative forcing (RF) coefficient, with noninformative priors being used for all other parameters. See Table 1 for details. RF and volcanic stratospheric aerosols (VOLC) are measured in Wm^{-2}. The Southern Oscillation Index (SOI) and Atlantic Multidecadal Oscillation (AMO) are measured as scaled indices. The AR(1) term denotes an autoregressive error coefficient. The implied TCR values at the bottom of the table are measured in °C and are obtained by multiplying the coefficient on RF by $F_{2\times}$ per eq. (5). The data have been centered, hence the lack of intercept, and comprise annual observations over 1866–2005.

recovery of posterior beliefs about TCR. These are summarised at the bottom of Table 3, while the full prior and posterior distributions are plotted in Fig. 1. We see that the posterior TCR distributions are generally clustered around a best estimate of 1.5 °C, with a 95% credible interval in the region of 1.1–1.8 °C, depending on the prior. Excepting the Strong Denier, these posterior beliefs about TCR fall comfortably within the IPCC "likely" range. However, the derived probability intervals are decidedly narrower and TCR values at the upper end of the spectrum are discounted accordingly.

Further insight into the updating behaviour of our stylised sceptics is provided by the recursive TCR estimates shown in Fig. 2. It is apparent that stronger convictions about one's prior beliefs (in the form of a smaller prior variance) have a greater dampening effect on posterior outcomes than the prior mean. For example, the Moderate Denier converges more rapidly to the noninformative distribution than the Strong Lukewarmer. However, most sceptics will converge to the noninformative distribution only after "observing' ' data from a number of decades. Note that this does not alter the conclusions that we are able to draw from our Bayesian analysis. As long as we have fully specified a prior that encapsulates a person's initial beliefs, then we should

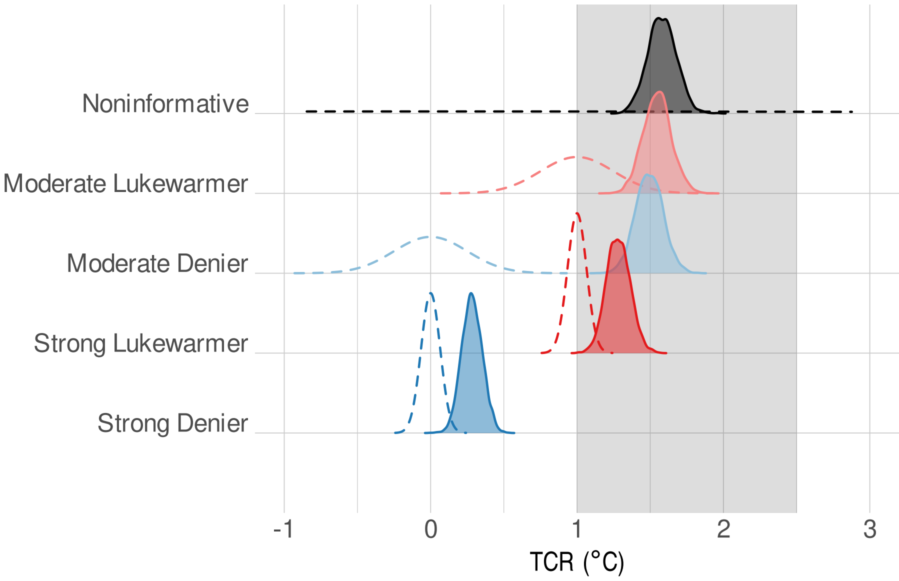

Fig. 1 TCR densities. Dashed lines denote priors, solid lines denote posteriors. The grey shaded region denotes the IPCC "likely" TCR range of 1.0–2.5 °C.

in principle treat the full historical dataset as new information for updating those beliefs.[11] Yet it does highlight the importance of using all the available instrumental climate data for building any kind of policy consensus. Limiting the sample period under observation to, say, the last 35 years would largely preclude the possibility of consensus formation. The tendency of some prominent sceptics to rely on satellite records of global temperatures — which only stretch back as far as 1979 — could be seen as anecdotal evidence in support of this claim (e.g. [51]). A similar argument could be made for a reliance on short-term climate trends and fluctuations that do accurately reflect longer-term trends. For example, the relatively brief "hiatus" in warming that followed the exceptionally strong 1998 El Niño event ([52]).

Returning to the question posed at the beginning of this paper: How much evidence would it take to convince climate sceptics that they are wrong about global warming? One way to reframe this question is to think about how much data a sceptic needs to observe before their best estimate of climate sensitivity begins to look reasonable to a mainstream climate scientist. For example, how long would it take before they obtained a mean posterior TCR of 1.3 °C or 1.5 °C? While it is possible to look at the sceptics' recursive TCR estimates using only historical data, we run into problems with the more extreme priors. In short, there is simply not enough historical data to overcome higher orders

[11] As a corollary, concerns over the use of the full historical dataset would only hold sway in cases where priors already incorporate information that has been obtained from applying the same model on a sub-sample of the dataset. In that case, we would need to exclude the sub-sample from the analysis to derive a valid posterior that avoids double counting.

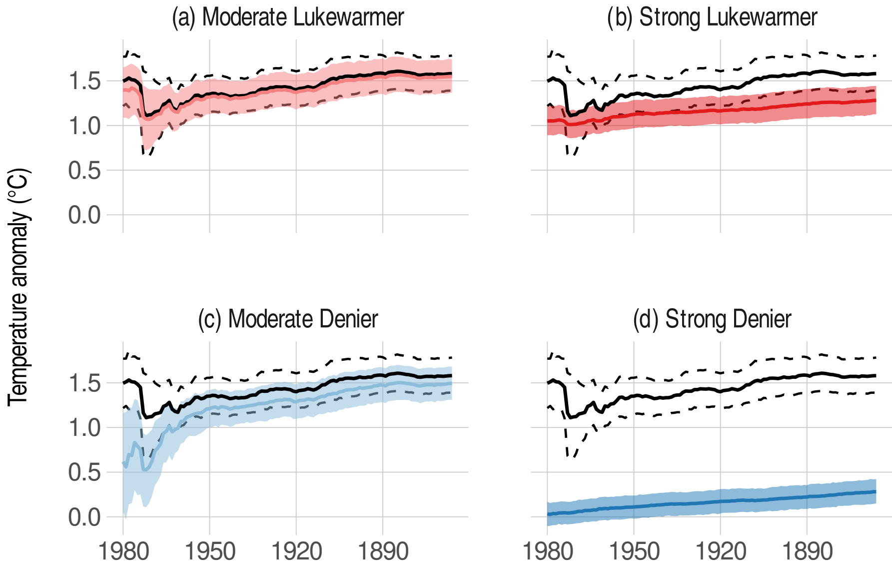

Fig. 2 Recursive TCR estimates. Solid lines denote means, shaded regions (or dashed lines) denote 95% credible intervals. The recursive estimates are obtained by running the regression in eq. (5) on an increasing subsample of the data. I start nearest to the present and move backwards in time, adding another year's worth of data at every iteration, until the full historical dataset is included. In each panel, the resulting posterior TCR estimate from a sceptic prior is contrasted with the noninformative case (in black).

of scepticism. I therefore simulate over 200 years' worth of global temperature and climate data using parameters obtained from the noninformative Bayesian regression in Table 3. I then use this simulated data to run a set of secondary regressions that are distinguished by a range of different sceptic priors on TCR. (This range is much more granular than my original four-sceptic typology.) Each regression is estimated recursively, incrementing one year at a time, until I obtain a posterior TCR distribution that has a mean value equal to the relevant target.

The results are shown in Fig. 3. While the instrumental climate record constitutes enough data to convince many sceptics in this hypothetical pool, it does not suffice in all cases. Similarly, although we expect that many present-day sceptics will eventually acquiesce their beliefs if climate change continues into the future, there remains a small group of hardcore sceptics who defiantly refuse convergence with the mainstream even if we project as far ahead as 2100. Such is the strength of their priors. Note further that the year of convergence is a non-linear function of prior strength, so that it becomes increasingly difficult to convince the marginal sceptic. The steady accumulation of evidence over time will inexorably bring more sceptics into the mainstream fold. But the delay between each round of new converts is increasing.

An implication of this thought experiment is the following. If someone is unpersuaded of the human influence on climate today — despite all of the

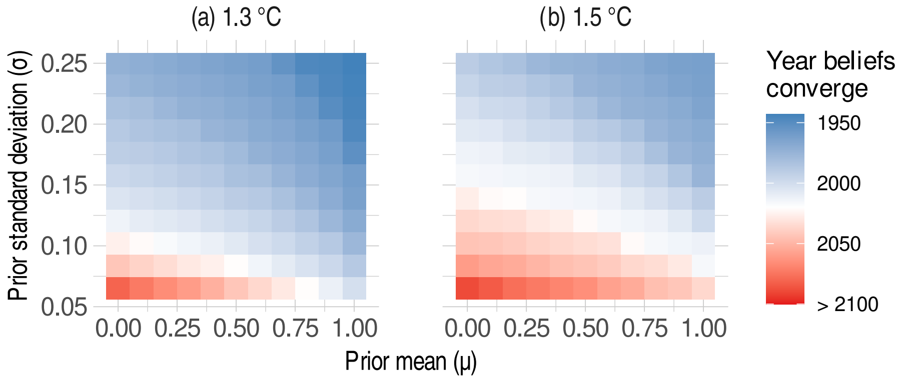

Fig. 3 When do sceptic beliefs about TCR converge with mainstream estimates? Axes denote the means and standard deviations of a range of normally-distributed sceptic priors on TCR. Convergence is defined as occurring when the mean posterior TCR for a particular prior equals the relevant target value, i.e. (a) 1.3 °C or (b) 1.5 °C. The year of convergence assumes a starting date of 1866 to coincide with the common historical dataset. Blue shading indicates that convergence is feasible with historically available data. Red shading indicates that convergence can only occur once additional data has been accumulated in the future.

available evidence — then there is a high probability that they will remain unconvinced for many years hence. The extent to which these extreme sceptics constitute a meaningful voting block is an open empirical question. However, it is striking to think that such individuals are already out of reach from the perspective of comprehensive climate policy. Even the accumulation of evidence over the next several decades may not be enough to convince them. Scientific communication efforts should be tailored appropriately, specifically targeting moderates for persuasion (e.g. lukewarmers) rather than engaging sceptics *en masse*.

5.2 Sensitivity analysis

I consider a number of alternative specifications to test the sensitivity of my findings. Table 4 summarises the resulting posterior TCR distributions that obtain under noninformative priors — see the Supplementary Material for full posterior distributions across all prior types. The general effect of these alternate specifications, regardless of prior, is to nudge the posterior TCR mean higher. We also see a widening of the posterior distributions, as some specifications explicitly introduce additional uncertainty into the estimation.

A first sensitivity check is motivated by the fact that HadCRUT4 is known to suffer from potential coverage biases due to incomplete placement of *in situ* thermometers. I therefore rerun the analysis with two alternate reconstructions of GMST. [45], hereafter CW14, correct for the gaps in the HadCRUT4 dataset by using an interpolation algorithm based on the "kriging" method. Similarly, the NASA Goddard Institute for Space Studies uses an extrapolation algorithm to overcome coverage bias in GISTEMP, its own GMST reconstruction.

Table 4 TCR: Sensitivity analysis and alternative specifications.

Key	TCR	Comment
CW14	1.6 (1.4, 1.9)	Alternative GMST series.
GISTEMP	1.8 (1.5, 2.0)	Alternative GMST series.
HadCRUT ME	1.6 (1.4, 1.8)	Measurement error in GMST data.
DF18	1.4 (0.9, 2.6)	Measurement error in forcings data.
MEA16 I	2.2 (1.9, 2.5)	Adjusted forcing efficacies (means).
MEA16 II	1.9 (-0.7, 3.4)	Adjusted forcing efficacies (distributions).
Anthro	1.6 (1.4, 1.8)	Separate anthropogenic from natural forcings.
CO_2	1.7 (1.3, 2.0)	Separate CO_2 from other forcings.

Notes: TCR means are given in °C, with 95% credible intervals in parentheses. The estimates above are computed using noninformative priors only. Full distributions for all prior types across all sensitivity runs are provided in the Supplementary Material. See main text for additional details.

Running the Bayesian regression model on these alternative series yields moderately higher TCR values compared to HadCRUT4. Under a noninformative prior, the posterior TCR means (and 95% Bayesian credible intervals) are 1.6 °C (1.4–1.9 °C) for CW14 and 1.8 °C (1.5–2.0 °C) for GISTEMP. Given that the explicit goal of this paper is to evaluate policy options from the perspective of climate sceptics, I continue using the results from the HadCRUT4 series as a default. Yet, it should be noted that this is a conservative choice that may, at least marginally, understate the true level of warming.

All three GMST reconstructions also provide estimates of measurement error. The Bayesian framework is ideally suited to incorporate such knowledge, since the nested model structure allows us to fully specify measurement error on the dependent variable within the regression model itself. Doing so in the present setup yields TCR estimates that are effectively identical to those presented in Table 3, namely 1.6 °C (1.4–1.8 °C). This is unsurprising once we recall that measurement error on the dependent variable is absorbed by the disturbance term of the regression model.[12] Since the Bayesian regression framework is primarily concerned with total model uncertainty, specifying the relative contribution of such measurement error to the overall disturbance doesn't meaningfully alter the analysis — though it may be useful for incorporating known sources of heteroscedasticity.[13] The primary regression results already have GMST measurement error "baked in" to the estimation, regardless of whether we define it explicitly or not.

The same could not be said for measurement error in the model explanatory variables — radiative forcing, most importantly — which needs to be accounted for explicitly. Fortunately, the Bayesian framework offers a natural

[12] For example, see p. 326 of [53]. To illustrate with a simple univariate case: The regression model can be written as $y_t \sim \mathcal{N}(\beta X_t, \sigma^2 + \omega_t^2)$, where $\sigma^2 = \text{Var}(\epsilon)$ is the variance of the error term and $\omega_t^2 = \text{Var}(\nu_t)$ is the variance of the measurement error on y_t. Together, ϵ and ν_t make up the overall disturbance of the regression.

[13] See [54] for a related discussion in a frequentist setting.

way to incorporate this type of uncertainty. I conduct a Monte Carlo simulation using the 1,000-member ensemble of forcing estimates from [47]; hereafter DF18. Specifically, I run my Bayesian regression model on each member of the DF18 ensemble separately — 1,000 different regressions with each taking their corresponding forcings as the true state of the world — before aggregating the posterior results into a single meta-distribution at the end.[14] The resulting posterior is wider, as expected due to the additional uncertainty. But the TCR mean and 95% credible interval of 1.4 °C (0.9–2.6 °C) are still well situated within the IPCC "likely" range.

Thus far, I have assumed that the different physical drivers that make up total radiative forcing have the same per-unit effect on GMST. Forcing agents that yield a similar radiative imbalance in Wm^{-2} are expected to result in similar feedbacks and responses in GMST. However, recent research has suggested that the warming efficacy of different forcing agents can, in fact, vary with factors like geography. Aerosol emissions, for example, are primarily concentrated in the mid-to-high latitudes of the Northern Hemisphere. The disproportionately large land mass in this region causes aerosol forcing to exhibit stronger feedback effects and an accelerated temperature response than if it were uniformly distributed across the globe [55]. The implications of such forcing inhomogeneity on climate sensitivity estimates are more fully explored by [56], hereafter MEA16. I adapt their results to construct an adjusted series of total radiative forcing, where each forcing agent is pre-multiplied by an appropriate efficacy coefficients (see Supplementary Material). Specifically, I consider two approaches. The first takes MEA16's mean efficacy estimates as given and ignores all modeling uncertainty in their results. The second explicitly accounts for modeling uncertainty in much the same way that was used to account for explanatory variable measurement error above; i.e. I conduct a Monte Carlo exercise that repeatedly samples from the t distributions underlying each forcing efficacy estimate and then combines the posterior results from many regressions into a single meta-distribution at the end. Consistent with MEA16, both approaches lead to a pronounced increase in the posterior TCR mean, with the Monte Carlo sampling approach further yielding a much wider credible interval. However, MEA16 note that data artefacts — e.g. small changes experienced by some forcing agents over their study period — automatically induce large uncertainties in the associated efficacy estimates. Combined with the fact that MEA16 obtain their results from a single climate model rather than a multi-model ensemble, this means that the unusually wide credible intervals of the latter Monte Carlo approach should be regarded with caution.

As final sensitivity test, I relax the constraint that all sources of radiative forcing have to be included in the regression model under the same composite RF term. Recall that this decision was motivated by the fact that the forc-

[14] This probabilistic approach is the standard Bayesian solution to dealing with measurement error in explanatory variables. In contrast, deriving consistent regression estimators when there is measurement error in explanatory variables can be a much more complicated affair in frequentist settings [53].

ing agents in my dataset are all defined in Wm^{-2}. Separating out individual forcings and then placing different priors on them will likely cause the model to become physically inconsistent.[15] Such admonishments notwithstanding, I implement two version of this unphysical model. The first separates out anthropogenic forcings (e.g. GHGs) from natural forcings (e.g. solar radiation). The second separates out CO_2 forcing from all other sources. In both cases, the subjective priors from Table 1 are placed on the isolated anthropogenic component, while all other variables take noninformative priors. Both sets of regressions yield very similar results to the main, physically-correct specification. If anything, isolating CO_2 on its own yields a higher posterior TCR for certain prior types. However, this latter implementation should be treated with caution for reasons previously described.

5.3 Future temperatures

Climate policy is largely predicated upon the risks to future generations. As such, any policy discussion must consider predictions that run many years into the future. TCR estimates are one means of gaining an insight into how global temperatures will evolve over the coming decades. A more explicit way of demonstrating this is by predicting temperatures until the end of the century.

While the trajectory of future radiative forcings is subject to much uncertainty, some guidance is available in the form of the IPCC's Representative Concentration Pathways [57]. These so-called "RCPs" describe a family of emissions scenarios, where total anthropogenic forcings evolves according to various economic, demographic and technological assumptions. Each RCP includes a core component of atmospheric CO_2 concentrations, while they all share a common prediction for radiative forcing due to solar activity. I take these series as the basis for constructing covariate vectors to predict temperatures until the year 2100. For the remaining explanatory variables — stratospheric aerosols, SOI and AMO — I take the mean historical values from my dataset. A summary of covariate vectors in 2100 for each RCP scenario is provided in the Supplementary Material.

Fig. 4 shows the temperature evolution for each RCP under the noninformative case, which I again take as the benchmark. As discussed in Section 2.2, it would be inappropriate to extrapolate my regression framework to scenarios that are characterised by significant changes in the rate of radiative forcing. The confounding effect of (unaccounted for) thermal inertia in the oceans would render these model predictions ill-conditioned. I therefore focus on RCPs 6.0 and 8.5, which maintain steady rates of forcing increase.[16] The principal message is that CO_2 concentrations must be constrained to well below RCP 6.0, if we are to avoid a 2 °C rise in global temperatures. Given the

[15] For the anthropogenic forcings, the use of a composite term also avoids introducing severe multicollinearity into the econometric estimation.

[16] Temperature predictions for RCPs 2.6 and 4.5 — depicting respective CO_2 stabilisation scenarios — are included in Fig. 4 for reference purposes only.

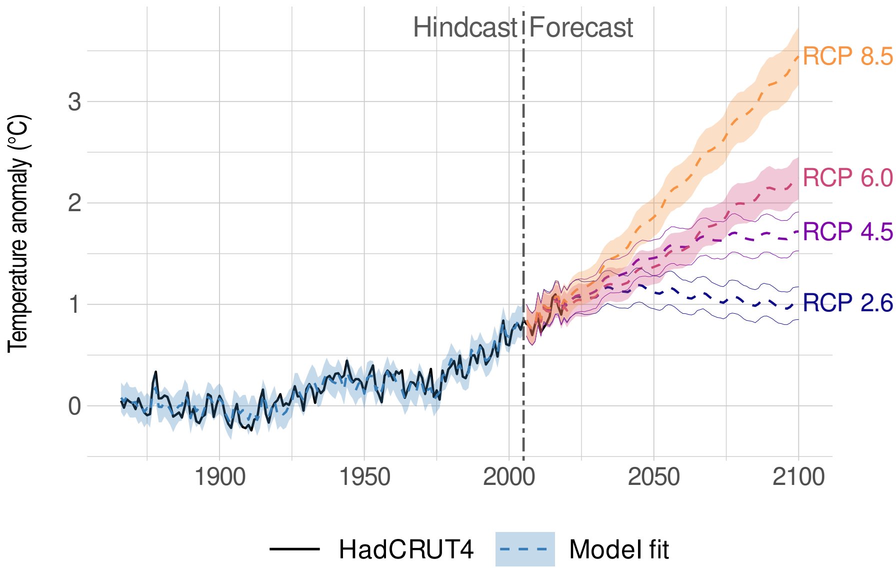

Fig. 4 Model fit and prediction: noninformative priors. Temperature anomaly relative to the 1871–1900 average. Shaded regions denote 95% credible intervals. Note that predictions for RCPs 2.6 and 4.5 are potentially ill-conditioned and are included for reference purposes only. See text for details.

prominence of this particular threshold in international climate treaties and the popular narrative, the result is a reinforcement of commonly cited emissions targets such as 450 and 540 ppmv. On the other hand, we can expect to breech even 3 °C by the year 2100 if we continue along a truly unconstrained emissions path à la RCP 8.5.

What of the predictions yielded by our group of climate sceptics? While it is straightforward to redraw Fig. 4 for each prior type, a more intuitive comparison can be made by looking at the full distribution of warming that each sceptic expects by the end of the century. Fig. 5 plots the predictive temperature density in the year 2100 for all prior types by RCP scenarios 6.0 and 8.5. Again, the data have a clear tendency to overwhelm even reasonably staunch forms of climate scepticism. Nearly all of the stylised sceptics would expect to breach the 2 °C threshold by 2100 under RCP 6.0, while a temperature rise of more than 3 °C is likely under under RCP 8.5. An exception can only be found in the form of the Strong Denier, whose extreme prior dominates the posterior in a way that obviates nearly all concern about large temperature increases.

5.4 Welfare implications and the social cost of carbon

Provided they consider enough data, we have seen that most climate sceptics should be able to agree that a 2 °C target requires limiting CO_2 concentrations

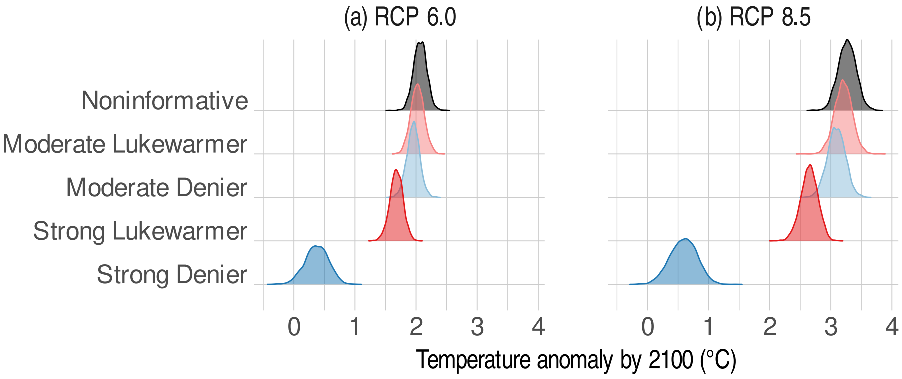

Fig. 5 Predicted temperature anomaly by 2100: all priors types. Points denote means and error bars denote 95% credible intervals.

to around 540 ppmv. However, whether someone actually subscribes to policy measures aimed at achieving the 2 °C goal is dependent on many things; their choice of discount rate, beliefs about the efficacy of policy, damage expectations, etc. Such issues are largely beyond the scope of this paper. Nonetheless, we may still gain a deeper insight into the welfare implications of our posterior TCR values by analysing their effect on the social cost of carbon (SCC). The SCC represents the economic costs associated with a marginal unit of CO_2 emissions. It can therefore be thought of as society's willingness to pay for the prevention of future damages associated with human-induced climate change.

Obtaining SCC estimates generally requires the use of integrated assessment models (IAMs), which are able to solve for optimal climate policy along a dynamic path by simulating across economic and climate systems. The PAGE model ([58], [59]) is ideally suited to our present needs. It is widely used as one of the major IAMs for evaluating climate policy ([60], [61]). More importantly, PAGE accepts random variables as inputs and yields the type of probabilistic output that is consistent with the rest of this paper. I take the posterior TCR distributions yielded by my Bayesian regression model and use these as inputs for calculating the SCC. The PAGE defaults are used for the remaining parameters.

Table 5 summarizes the SCC distributions across all prior groups in 2005 US dollars. The full probability distributions are highly skewed and characterised by extremely long upper tails (see the Supplementary Material). This is largely due to the fact that PAGE allows for the possibility of major disruptions — e.g. melting of the Greenland ice sheet — at temperatures above 3 °C. Such low probability, high impact events would yield tremendous economic losses and result in some extreme SCC values as a consequence. Note too that the frequency of these events are more common in my adapted version of PAGE, since I replace the default triangular (i.e. bounded) TCR distribution with the posterior TCR distributions from my model. The latter are approximately normally distributed, thus permitting small but positive weight in the tails.

Table 5 Social cost of carbon (US$2005 per ton).

	Mean	Median	95% Prob. Interval
Noninformative	79	41	(12, 168)
Moderate Lukewarmer	65	39	(11, 160)
Strong Lukewarmer	48	26	(7, 107)
Moderate Denier	68	36	(10, 149)
Strong Denier	2	1	(0, 5)

Notes: Results for each agent type are obtained from 10,000 simulation runs of PAGE. Posterior TCR distributions serve as key inputs to the model, while the remaining parameters are set to the PAGE model defaults.

For this reason, I provide both the mean and median SCC values alongside the 95% probability interval.

Excepting the Strong Denier, the SCC for all prior types is comfortably larger than zero. The mean value ranges from $48 to $79 per ton (2005 prices), while the 95% probability interval extends from around $7 to upwards of $107 per ton. These results are consistent with the SCC estimates found within the literature. For example, an influential synthesis review conducted by the United States government under the Obama administration established a mean SCC value of $12–$62 per tonne (2007 prices), depending on the preferred discount rate ([61]). The encouraging point from a policy perspective is that such congruence exists despite the fact that the analysis proceeds from an initial position of scepticism. Another way to frame the SCC estimates presented here is to imagine that each prior type represents an equal segment of a voting population. We would then expect to see broad support for a carbon tax of at least $20–$25. While such a thought experiment clearly abstracts from the many complications that would arise from free-riding and so forth, again we see that nominal climate scepticism does not correspond to a mechanical dismissal of climate policy.

6 Discussion

We have seen that a non-trivial carbon price is consistent with a range of contrarian priors once we allow for updating of beliefs and, crucially, consider enough of the available data. An optimist might interpret these findings as a sign that common ground on climate policy is closer than many people think. On the other hand, they may also help to explain why the policy debate is so polarised in the first place. As all intermediate positions are absorbed into the mainstream, only the most hardcore sceptics will remain wedded to their priors. Such a group is unlikely to brook any proposals for reduced carbon emissions and virtually no amount of new information will convince them otherwise. Taken together with the persistent scepticism that one sees in actual polling data (e.g. [8]), it then becomes reasonable to ask whether real-life climate sceptics hold such extreme views? For that matter, are they numerous or vocal enough to prevent political action ([16])? Such considerations are reinforced by the idealized nature of the analysis until now. Irrespective of the scientific merit of working through such a set-up, normal people clearly do not update their priors in lockstep with a Bayesian regression model, supported by large dataset of time-series observations.

A natural starting point for thinking about these issues is to take a closer look at the mechanisms underlying posterior agreement formation. The notion that partisans should converge toward consensus with increasing information has long been taken as a logical consequence of Bayes' theorem. Indeed, empirical evidence to the contrary has been cited as a weakness of the Bayesian paradigm and its relevance to real-life problems (e.g. [62]). This is a misconception. Nothing in the Bayesian paradigm precludes the possibility of diverging opinions in the face of shared information ([63], [64]). It may even be the case that the same information has a polarising effect on individuals, pushing them towards opposite conclusions. This is perhaps most easily shown by incorporating perceptions of trust and source credibility into our Bayesian model. In other words, we must broaden our conception of someone's "prior" so that it describes not only their existing beliefs about some phenomenon S, but also the credibility that they assign to different sources of information about S.

Consider an example, which is closely adapted from a related discussion in [63]. Al, Bob and Christie hold different beliefs about climate change. Al is a "warmist", Bob is a "lukewarmer" and Christie is a "denier". These labels are encapsulated by the prior probabilities that each person assigns to climate sensitivity S, which we assume for simplicity is either high or low: $S \in S_L, S_H$. Denote by I an individual's prior information about the world. Then, indexing by the first letter of their names, we summarise their prior beliefs about climate change as the following probabilities: $P(S_H|I_A) = 0.90$, $P(S_H|I_B) = 0.40$, and $P(S_H|I_C) = 0.10$.

Suppose that the IPCC now publishes its latest assessment report, wherein it claims that climate sensitivity is high. How do Al, Bob and Christie respond to this new data, $D = D_H$? It turns out that the answer hinges on the regard that each individual holds for the IPCC itself. For example, let us say that all three individuals agree the IPCC would undoubtedly present data supporting a high climate sensitivity if that were the true state of the world, i.e. $P(D_H|S_H, I_A) = P(D_H|S_H, I_B) = P(D_H|S_H, I_C) = 1.00$. However, they disagree on whether the IPCC can be trusted to disavow the high sensitivity hypothesis if the scientific evidence actually supported a low climate sensitivity. Despite their different beliefs about climate sensitivity, assume that Al and Christie both regard the IPCC as an upstanding institution that can be trusted to accurately represent the science on climate change. In contrast, Bob is dubious about the motives of the IPCC and believes that the organisation is willing to lie in advancement of a preconceived agenda. Representing these beliefs in terms of probabilities, we have $P(D_H|S_L, I_A) = 0.05$, $P(D_H|S_L, I_B) = 0.89$, and $P(D_H|S_L, I_C) = 0.05$.

Recovering the posterior beliefs about climate sensitivity for our three individuals is now a simple matter of modifying Bayes' theorem to account for each person's relative trust in the IPCC. For Al, we have

$$\begin{aligned}P(S_H|D_H, I_A) &= \frac{P(D_H|S_H, I_A)P(S_H|I_A)}{P(D_H|S_H, I_A)P(S_H|I_A) + P(D_H|S_L, I_A)P(S_L|I_A)} \\ &= \frac{1.0 \times 0.9}{1.0 \times 0.9 + 0.05 \times 0.1} \\ &\approx 0.98.\end{aligned}$$

Similarly, we obtain posterior probabilities of 0.43 for Bob and 0.69 for Christie.

Taking a step back, Al now believes even more strongly in the high climate sensitivity hypothesis, having raised his subjective probability for S_H from 90% to 98%. Christie has experienced a still greater effect and has updated her subjective probability for S_H from 10% to 69%. She now attaches a larger probability to the high sensitivity hypothesis than the low sensitivity alternative. However, the same cannot be said of Bob, who has not been swayed by the IPCC report in the slightest. Both his prior and posterior probabilities suggest that S_H only has an approximately 40% chance of being true. Bob's extreme mistrust has effectively led him to discount the IPCC's high sensitivity claim in its entirety.

Extending the above framework to account for increasing granularity is conceptually straightforward. The principal insight remains the same: Trust is as much a determinant of whether beliefs are amenable to data — and whether individuals converge towards consensus — as the precision of the data itself. Such an extension seems especially relevant to the climate change debate given the sense of scientific distrust that pervades certain segments of society ([65], [66], [67], [68], [69]). Indeed, recent research supports the notion that distrust of scientists is causing belief polarization about climate change in some demographic groups, even as scientific evidence may increase consensus in others ([70], [71]). Similar "backfire" effects have been well documented in other fields ([72], [73]).

Perhaps the most important feature of generalising the Bayesian framework in this way is that it offers a bridge between competing explanations of climate scepticism as a social phenomenon. Whereas the so-called "deficit model" posits a lack of scientific knowledge and understanding as key drivers of scepticism, advocates of the "cultural cognition" theory argue that group identity and value systems are more relevant ([9], [10], [74]). A Bayesian model that incorporates perceptions of source credibility is able to accommodate both camps. Exposure to new scientific evidence can ameliorate a person's scepticism, but only if their priors allow for it. This includes factors like cultural identity and whether they cause us to discount some sources of information more than others.[17]

[17] While the precise theoretical development differs from the framework presented here, I would note the closely-related concept of Bayesian networks ([75]). Indeed, [70] use a

7 Concluding remarks

The goal of this paper has been to explore the way in which prior beliefs affect our responsiveness to information about climate change. The Bayesian paradigm provides a natural framework and I have proposed a group of stylised sceptics to embody the degrees of real-world climate scepticism. The headline finding is that subjective sceptic priors are generally overwhelmed by the empirical evidence for climate change. Once they have updated their beliefs in accordance with the available data, most sceptics demonstrate a clear tendency to congregate towards the noninformative case that serves as an objective reference point for this study. My primary regression specification yields a posterior TCR mean and 95% credible interval of 1.6 °C (1.4–1.8 °C) under the noninformative prior. This distribution sits comfortably within the IPCC's "likely" TCR range of 1.0–2.5 °C and is robust to variety of sensitivity checks. Indeed, accounting for factors that could conceivably affect the results — alternate data sources, adjusted forcing efficacies, measurement error, etc. — tends to nudge the mean TCR estimate upwards.

Unsurprisingly, given their congruence with mainstream estimates, I show that the updated beliefs of various sceptics are generally consistent with a social cost of carbon of at least US$25 per ton. Only those with extreme *a priori* sceptic beliefs would find themselves in disagreement. Or, feel any confidence in the notion that unfettered emissions growth will not lead to substantial future warming. This suggests that a rational climate sceptic, even one that holds relatively strong prior beliefs to begin with, could embrace policy measures to constrain CO_2 emissions once they have seen all of the available data. At the same time, perhaps the most salient finding of this paper is that belief convergence is a non-linear function of prior strength. Anyone that remains unconvinced by the available data today is unlikely to converge with the mainstream consensus for many years hence. Their implied priors are of such a strength that even decades more of accumulated evidence may not be enough to convince them. Fully disentangling the root causes of such information immunity — whether climate sceptics are extremely sure of their priors, distrustful of scientists and other experts, or some combination thereof — remains an important area for future research.

Declarations

The author has no relevant financial or non-financial interests to disclose. All code and data for the study are available at `https://github.com/grantmcdermott/sceptic-priors`.

Bayesian network approach in an experimental setting to document (rational) belief polarization after individuals are presented with evidence about climate change. Mistrust of climate scientists is a primary source of the polarization in their study.

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