Updating climate beliefs based on latest IPCC report points to increased willingness to act

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Abstract

We assess how changes in the scientific consensus around equilibrium climate sensitivity (ECS), as captured by the IPCC's Fifth (AR5) and Sixth (AR6) Assessment Reports, impact policymakers' willingness to take climate action. Taking the IPCC's reports at face value, the ECS estimates in AR6 would have lowered a policymaker's willingness to act on climate relative to AR5 due to a narrower "likely" range. However, Bayesian updating may reverse this conclusion. An accuracy-motivated policymaker who was not convinced to take greater climate action by the evidence in AR5 may be more likely to strengthen their policy views by the evidence in AR6.

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Equilibrium climate sensitivity (ECS) parameterizes the estimated change to global average temperatures over the course of centuries that will be caused by a doubling of concentrations of carbon dioxide (CO_2) in the atmosphere (Proistosescu and Huybers, 2017). The earliest expert assessment, conducted by the U.S. National Academy of Sciences in 1979, arrived at a "likely" range of $1.5°C - 4.5°C$ (Charney et al., 1979). While the definition of what it means to be "likely" has become more precise over time (Bradley, 2017)—the Intergovernmental Panel on Climate Change (IPCC) now defines it as occurring with at least a 66% probability (IPCC, 2010)—the range itself had remained steady at $1.5°C - 4.5°C$ for most of the IPCC's history (IPCC, 2001; IPCC, 1995; IPCC, 1990). The first exception came in the Fourth Assessment Report, which narrowed the range to $2°C - 4.5°C$ (IPCC, 2007), only to widen it again in the Fifth Assessment Report (AR5) to $1.5°C - 4.5°C$ (IPCC, 2013). In part based on a comprehensive re-assessment of the ECS evidence (Sherwood et al., 2020), the IPCC has since narrowed the range in its Sixth Assessment Report (AR6) to $2.5°C - 4°C$ (IPCC, 2021).

This paper focuses on the way that these changes in ECS estimates are assimilated by a policymaker and how this then alters their willingness to act to prevent climate change, as measured by the amount they would be prepared to pay to prevent all future climate change damages.

We consider two separate situations. In the first, the policymaker simply adopts the latest IPCC's range as their own. In this case, they would interpret the AR5 widening of the range as a prompt to increase the willingness to act to cut CO_2 emissions (Freeman et al., 2015). Uncertainty, after all, is costly, with ECS uncertainties among the most important factors in strengthening the economic case for cutting CO_2 emissions (Moore et al., 2024; Weitzman, 2009). Conversely, this might turn the step taken in AR6 into "good news"— as the narrowing of ECS range from AR5 to AR6 now suggests a lowered *need* to act. Our first result confirms that this is the case.

Our primary contribution—presented as the second result—comes from recognizing that policymakers who read either AR5 or AR6 have prior beliefs about the ECS. Under such circumstances, they may choose to Bayesian-update their position in light of new expert information. We assume that such a policymaker is accuracy-, rather than directionally-, motivated (Druckman and McGrath, 2019). They evaluate information in an 'objective manner' that is not influenced by their prior belief, and do not suffer from discomfirmation bias by rejecting information that does not support their existing policy position. Instead they apply Bayes' Theorem rationally and accurately based on the scientists' own assessment of the remaining uncertainties surrounding the ECS.[1]

We find the necessary and sufficient conditions under which such an accuracy-motivated Bayesian policymaker who previously had a willingness to act below that implied by either AR5 or AR6—an assumption which appears consistent with existing policy (Drupp et al., 2024)—will then increase their willingness to act due to the IPCC updating its ECS range. Contrasting with our first result, we prove that AR6 has strictly greater power than AR5 to cause such a policymaker to take stronger action.

Our results have another important implication. Deryugina and Shurchkov (2016) observe that, when shown the scientific consensus on climate change, people are "... more likely to report believing that climate change was already underway and that it was caused by humans. However, their beliefs about the necessity of making policy decisions and their willingness to donate money to combat climate change were not affected" (*ibid.*, p.1). They explain that the "... lack of updating based on objective information in this context is

[1]This also contrasts with, for instance, Augenblick et al. (2025), who examine how people apply Bayes' Theorem imprecisely when updating their views.

consistent with a number of explanations, including strong priors, self-justification bias, selective attention, cultural norms, partisan bias, and information discounting" (*ibid.*, p.12). Yet, within the Bayesian updating model that we present, such behavior can also be explained fully rationally. An increased expectation of future temperature changes can co-exist with a lowered willingness to act if new information results in sufficiently more precise estimates of the ECS.

1. Policy response to new scientific information

Under a set of plausible assumptions, the willingness to act to fully prevent future climate change damage is monotonically increasing both in the expected ECS value and its uncertainty. For the former, the more we expect human greenhouse gas emissions to increase global temperatures, the more pressing climate change becomes as a policy priority. But "... the economic case for stringent GHG abatement cannot be made based on 'most likely outcomes' ... (instead) any case for stringent abatement must be based on the possibility of a catastrophic climate outcome" (Pindyck, 2013, pp. 234–5). The more uncertain we are about the ECS, the more we will do to prevent future emissions in an attempt to avert the most damaging plausible outcomes. Mathematically, we denote ECS here by T, and it has previously been shown that the willingness to act is monotonically increasing in $E[T^2] = E^2[T] + \mathrm{Var}[T]$ (Freeman et al., 2015; see also Appendix A).

The central purpose of this paper is to consider how an accuracy-motivated policymaker will re-evaluate their willingness to act when presented with the latest scientific consensus evidence on the ECS. Since this is determined through $E[T^2]$, it is necessary to consider how the probability distribution for T changes based on this new information. This task requires us to clearly differentiate between five distinct probability density functions. The first two of these capture the distribution of T that can be inferred from the IPCC's AR5 and AR6 reports (pdf1 and pdf2, respectively). Our first result shows that, because the spread of ECS estimates is much narrower in AR6 than AR5 even for a higher mean, the willingness to act is lower under AR6 than under AR5. Stated mathematically, this is equivalent to saying that $E[T^2]$ is higher under pdf1 than pdf2.

IPCC reports, though, feed into the policy process through the human actions of policymakers who do not receive these reports with a previous blank slate of opinions on matters related to the ECS. Specifically, we focus on policymakers with a "low prior" in the sense that $E[T^2]$ is lower under their initial beliefs (pdf3) than either pdf1 or pdf2, which would therefore result in the policymaker initially taking actions below what AR5 or AR6 would justify. The final two probability distributions that we consider assume that the policymaker is given either AR5 or AR6 to read, and that they then Bayesian update their beliefs based on this report.[2] We assume that that they undertake this updating in a way that is fully accuracy-motivated, that they apply Bayes' Theorem without behavioral biases or errors, and that they accept the IPCC's estimates of the ECS as presented. They use Bayes' Theorem in this way because "French (1985), Lindley (1985), and Genest and Zidek (1986) all conclude that for the typical risk analysis situation, in which a group of experts must provide information for a decision maker, a Bayesian updating scheme is the most appropriate method" (Clemen and Winkler, 1999, p.190; see also Vivalt and Coville, 2023). Their Bayesian posterior distribution is denoted by pdf4 (pdf5) if they revised their views based on AR5 (AR6).

Our second result is that AR6 has strictly stronger power to persuade this policymaker to increase their willingness to act than does AR5. This is paradoxical because, when taken at face value, AR6 is "good

[2]We do not consider the situation where the policymaker is initially given AR5 to update their beliefs and then, subsequently, AR6 to update their beliefs for a second time. This is because the overlap of information in the two reports is too great to separate out within this type of analysis. Similarly, we assume that the forecasting errors between the policymaker's prior and either AR5 or AR6 are independent from each other (Appendix B).

news" compared to AR5. Yet this result follows from the way that the policymaker's estimates of $E[T]$ and $\mathrm{Var}[T]$ change under a Bayesian approach and how this contrasts with the mean and variance of the expert opinion when taken in isolation.[3]

2. The scientific consensus and the policymaker's prior

To establish and quantify these results, we must first parameterize pdf1, pdf2 and pdf3 and then, in the next section, use Bayesian updating under expert information to derive pdf4 and pdf5.

pdf1. We parameterise the relevant section of AR5 (IPCC, 2013, Section TS5.3) following a lognormal distribution (Sherwood et al., 2020; Wagner and Weitzman, 2018; Weitzman, 2009; Weitzman, 2007), by setting $\ln(T) \sim N(\phi_{AR5}, \Sigma^2_{AR5})$ for expected value $\phi_{AR5} = 0.9983$ and standard deviation $\Sigma_{AR5} = 0.5742$ of the variable's natural logarithm. This sets the expected value of the ECS $E_{AR5}[T] = 3.2°C$ and its standard deviation $T = 2°C$, and captures that the distribution is heavy-tailed. Consistent with AR5, there is a 66% chance that T lies in the $1.5°C - 4.5°C$ range, a less than 5% chance that $T < 1°C$ and a less than 10% chance that $T > 6°C$.[4]

pdf2. Similarly, for the relevant section of AR6 (IPCC, 2021, Section TS3.2.1), set $\ln(T) \sim N(\phi_{AR6}, \Sigma^2_{AR6})$ for parameters $\phi_{AR6} = 1.1654$ and $\Sigma_{AR6} = 0.2390$, so that the expected value is $E_{AR6}[T] = 3.3°C$ and the standard deviation is $T = 0.8°C$. This is consistent with the AR6 assessment that there is at least a 66% chance that T lies in the $2.5°C - 4°C$ range, a greater than 90% chance that T lies in the $2°C - 5°C$ range, that there is a less than 1% chance that $T < 1.5°C$ and that $T = 5°C$ is, with medium confidence, at the "upper end of the very likely range" (IPCC, 2021, Section TS3.2.1; Bradley et al., 2017).[5]

pdf3. The policymaker's Bayesian prior distribution for T is also assumed to be lognormally distributed, $\ln(T) \sim N(\mu, \sigma^2)$ with $\mu = 0.3466, \sigma = 0.8326$. Their beliefs correspond to a mean and standard deviation of $T = 2°C$. As a consequence, they think there is a 4.1% chance that $T > 6°C$, a 39.0% belief that it lies in the AR5's central range of $1.5°C - 4.5°C$, and a 33.9% chance that $T < 1°C$. This policymaker is therefore moderately less concerned about the potential climatic effects of greenhouse gas emissions than the IPCC consensus under either report.

We plot the AR5 distribution (pdf1) in panels (a)–(b) of Fig. 1. where the former shows the full distribution and the latter the right-hand tail. Similarly, we plot the AR6 distribution (pdf2) in panels (c)–(d) of Fig. 1. The policymaker's prior distribution (pdf3) is plotted in all four panels. For a lognormal distribution, $E[T^2] = \exp(2(\phi + \Sigma^2))$. As $\phi_{AR5} + \Sigma^2_{AR5} = 1.328 > 1.223 = \phi_{AR6} + \Sigma^2_{AR6}$, $E_{AR5}[T^2] > E_{AR6}[T^2]$. If the policymaker were, on reading the IPCC reports, to just accept these implicit distributions in AR5 or AR6 as given, the change in ECS description in AR6 reduces the willingness to act compared to AR5 because the increased precision offsets the small increase in mean estimate of T. This is our first result. The policymaker's prior (pdf3) is a "low prior" in that their willingness to act, which is determined by $\mu + \sigma^2 = 1.040$, lies below that implied by the ECS descriptions in either AR5 (pdf1) or AR6 (pdf2).

[3] We stress that our results focus on ECS estimates alone. A better quantification of damages, for example, or any number of other updates between AR5 and AR6, will also heavily impact on the Social Cost of Carbon (Moore et al., 2024; Hänsel et al., 2020; Rennert et al., 2022).

[4] Specifically, 66.0%, 4.1%, and 8.4%, respectively.

[5] Specifically, 67.4%, 94.4%, 0.1% and 96.8%, respectively.

3. Change in a Bayesian policymaker's willingness to act

In light of the expert opinion contained in a new version of an IPCC report, an accuracy-motivated Bayesian policymaker will update their beliefs in a way that is related to, but clearly distinct from, how one would update beliefs when encountering new empirical data (e.g., Clemen and Winkler, 1999; Genest and Zidek, 1986; Morris, 1974); see Appendix B.

pdf4. After reading AR5 (but not AR6), the posterior distribution of the policymaker is lognormally distributed $\ln(T) \sim N(\mu'_{AR5}, \sigma'^2_{AR5})$ with $\mu'_{AR5} = 0.7882$ and $\sigma'_{AR5} = 0.4727$. AR5 moves the centre of the distribution of the posterior to the right: $E[T]$ increases from $2°C$ to $2.46°C$. However, the tail of the posterior is thinner than the tail of the prior in pdf3; Prob$(T < 6°C)$ falls from 4.1% to 1.7%.

pdf5. After reading AR6 (but not AR5), the posterior distribution of the policymaker is lognormally distributed $\ln(T) \sim N(\mu'_{AR6}, \sigma'^2_{AR6})$ with $\mu'_{AR6} = 1.1030$ and $\sigma'_{AR6} = 0.2297$. AR6 moves the centre of the distribution of the posterior further to the right than AR5 did: $E[T]$ now increases to $3.09°C$. However, the right hand tail of the posterior becomes even thinner than before as Prob$(T < 6°C)$ falls to 0.1%.

We plot the posterior probability distribution after reading AR5 (pdf4) in panels (a)–(b) of Fig. 1., where the former shows the full distribution and the latter the right-hand tail. Similarly, we plot the posterior probability distribution after reading AR6 (pdf5) in panels (c)–(d) of Fig. 1.

We now draw distinctions between three separate effects: (i) that the policymaker has a low prior; (ii) that receiving an IPCC report increases the policymaker's expected ECS; and (iii) that receiving an IPCC increases the policymaker's willingness to act. As defined earlier, condition (i) is equivalent to $E[T^2]$ being lower under pdf3 than both pdf1 and pdf2. (ii) is equivalent to $E[T]$ being higher under pdf4 and/or pdf5 than under pdf3. (iii) is equivalent to $E[T^2]$ being higher under pdf4 and/or pdf5 than under pdf3. More formally, the policymaker has a low prior if and only if $\phi > \mu + \sigma^2 - \Sigma^2$. In Appendix B, we show that the other two conditions are given by (ii) $\phi > \mu + 0.5\sigma^2$ and (iii) $\phi > \mu + \sigma^2$.

These relationships show that the assumption that the policymaker has a low prior is not, on its own, sufficient for either the second or third conditions to hold.[6] In addition, while expert uncertainty around $\ln(T)$ (as captured by Σ in pdf1 and pdf2) will directly influence the policymakers willingness to act if they adopt the IPCC's assessment as their own, this variable does not influence whether or not a Bayesian policymaker will be increase their mean estimate of the ECS, or be more willing to act, after reading an IPCC report; conditions (ii) and (iii) are not a function of Σ. This is because a change in Σ has offsetting effects. The more certain the experts are in their estimate, the more the policymaker will change their estimate of the mean of $\ln(T)$ towards the scientific consensus. However, the more certain the experts are, the narrower the posterior distribution of $\ln(T)$ will be. These two effects exactly offset in their influence on both $E[T]$ and $E[T^2]$.

Interpreting this within the parameterizations in this paper, $E[T]$ increased in both cases in the posterior (pdf4 and pdf5) relative to the prior (pdf3), but this need not always be the case. For the third condition, under pdf3, $\mu + \sigma^2 = 1.040$, and so the assessment of the ECS in AR5 ($\phi_{AR5} = 0.9983$) does not increase their willingness to act on climate action. By contrast, the evidence in AR6 ($\phi_{AR6} = 1.1654$) would. This is somewhat paradoxical given our first result. More generally, as $\phi_{AR6} > \phi_{AR5}$, AR6 has strictly more power

[6]In Appendix B we prove that these three, and two other, related conditions are clearly distinct in the sense that none is a necessary and sufficient condition for any other.

to persuade the policymaker to increase their willingness to pay to prevent future climate damage than AR5 would if the policymaker is presented with only one of these reports.

4. Conclusion

A range of sensitivity analysis, available on request from the authors, shows that our two general conclusions hold under broadly relevant assumptions. This should not be surprising, as the intuition is both straightforward and generalizable to other settings. When the policymaker with a low prior Bayesian updates their beliefs, their mean estimate of T is likely (but not certain) to increase, while Bayesian posteriors will be more precise than their priors. Therefore, $E[T^2] = E^2[T] + \text{Var}[T]$ generally has offsetting terms that support our second result. The overall impact of the Bayesian updating process on the willingness to act, thus, might be considered ambiguous. We here show that ECS estimates in AR6 lead to a lower willingness to act than those in AR5 without Bayesian updating, while the ECS estimates in AR6 nevertheless have strictly greater power to persuade the policymaker to change their policy views in favor of greater willingness to act on climate policy.

By considering what happens when policymakers Bayesian update their views on the ECS after receiving new scientific information, we speak to two related areas of the literature. First, the way that IPCC updates to expected ECS values, uncertainty ranges, and confidence intervals are presented, and communicated have been shown be crucial to how policymakers perceive and, ultimately, act on the results (Kopp et al., 2023; Bradley et al., 2017). Yet those moderately hesitant to embrace climate-scientific results have been shown to be more willing to believe in climate change after reading scientific evidence, yet no more willing to take action to prevent it (Lewandowsky, 2021; Kahan, 2017; Bolsen and Druckman, 2016; Deryugina and Shurchkov, 2016). Our results provide a formal framework that reconciles these findings. While there are barriers aplenty to fully implementing anything resembling “rational” climate policy, this understanding of how policymakers use new information opens doors for further research on how the IPCC should report the latest scientific consensus on climate sensitivity estimates.

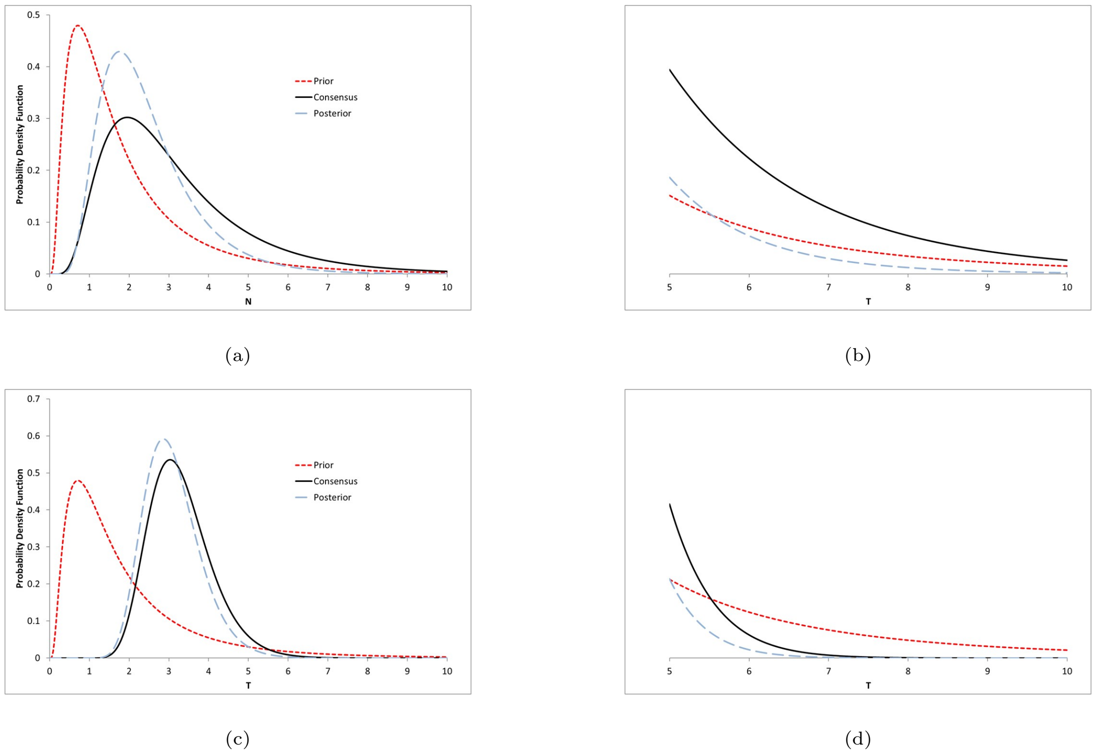

Figure 1: **a**, The full probability density functions for the prior (pdf3) and posterior distributions (pdf4) of the policymaker and the evidence in AR5 (pdf1). **b**, The right-hand tail of the PDFs for the prior and posterior distributions of the policymaker and the evidence in AR5. **c**, The full PDFs for the prior (pdf3) and posterior distributions (pdf5) of the policymaker and the evidence in AR6 (pdf2). **d**, The right-hand tail of the PDFs for the prior and posterior distributions of the policymaker and the evidence in AR6.

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Appendices

Appendix A Willingness to act and $E[T^2]$

In this Appendix A, we outline an earlier result (Freeman et al., 2015), which shows that the willingness to pay to avoid all future climate damage is, under reasonable assumptions, monotonic increasing in $E[T^2]$.

A.1 Assumptions

Three assumptions are necessary.

1. There is a single variable, T, that can be used to empirically quantify the scale of the climate change threat. Higher positive values of T correspond to worse outcomes and $T = 0$ represents no damages. In the context of this paper, this is taken to be the equilibrium climate sensitivity (ECS).
2. The value of T is currently unknown. In the absence of perfect foresight, the policymaker makes decisions on the basis of their beliefs about T. The policymaker has a prior probability density function (pdf) for T, and experts also present their evidence as a pdf on T through IPCC WG1 reports. After hearing the evidence, the policymaker uses Bayes' Theorem to update their beliefs and forms a posterior distribution on T. They take a fully accuracy-motivated approach to assimilating the evidence in the IPCC reports.
3. A standard economic model is used to determine the policymaker's willingness to act to either fully prevent future climate change damages or take no mitigative action.

A.2 The standard economic model

With no threat from climate change, per-capita real consumption at time t would be y_t^*. However, the harm done by climate change reduces per-capita real consumption to $y_t = (1 - D(T))\, y_t^*$ for some damage function $D(T) \in [0, 1)$ that increases with T when T is positive, and where $D(T) = 0$ if and only if $T = 0$. This damage function captures all future costs to society (environmental, health, mortality, etc.) in terms of the consumption numeraire. To deduce the willingness to act, we assume that the policymaker has a time-separable logarithmic utility function of consumption. This utility function is applied to global average real per-capita consumption levels: the policymaker evaluates benefits and losses to other countries and future generations as if they affected their own community directly. It follows that expected utility will be the same whether the policymaker incurs the cost p to fully prevent future climate change damages or not:

$$\ln(y_0 - p) + e^{-\rho t} E[\ln(y_t^*)] = \ln(y_0) + e^{-\rho t} E[\ln((1 - D(T))\, y_t^*)], \tag{1}$$

where ρ is the rate of pure time preference and y_0 current consumption. Simple rearrangement then gives:

$$\ln\left(\frac{y_0 - p}{y_0}\right) = e^{-\rho t} E\left[\ln(1 - D(T))\right]. \tag{2}$$

Assume $\rho = 0$ throughout as the directional change in willingness to act after receiving expert testimony does not depend on this constant. The policymaker and the IPCC agree on the utility function and the damage function and disagree only in their assessment of the likely realization of T.

Let $\psi(T) = -\ln(1 - D(T))$, which is monotonic increasing in T when T is positive. From equation (2) with $\rho = 0$, $p/y_0 = 1 - \exp(-E[\psi(T)])$ and hence p/y_0 is monotonic increasing in $E[\psi(T)]$. There are three sets of expectations of $\psi(T)$ that it will be necessary to consider; the prior expectation of the policymaker before hearing the scientific evidence, $E^f[\psi(T)]$; the expectation of the experts, $E^{f^c}[\psi(T)]$; and the expectation of the policymaker after hearing the evidence, $E^g[\psi(T)]$. These reflect the prior, $f(T)$, scientific consensus, $f^c(T)$, and posterior $g(T)$ probability density functions that are assigned to T. It is well known that $E^g[\psi(T)] > E^f[\psi(T)]$ for all monotonic increasing $\psi(T)$ if and only if $g(T)$ first order stochastically dominates $f(T)$. By contrast, if $g(T)$ does not first order stochastically dominate $f(T)$, then we cannot be sure that $E^g[\psi(T)] > E^f[\psi(T)]$, or, equivalently, that the willingness to act of the policymaker will increase as a consequence of hearing the scientific evidence. The fact that Bayesian posteriors are more precise than Bayesian priors means that this stochastic dominance condition will frequently not hold and therefore there is ambiguity over whether the policymaker's willingness to act will increase as a consequence of hearing the expert testimony. This is the central feature that is examined in this paper.

If $f^c(T)$ first order stochastically dominates $f(T)$, then the experts will assign a higher willingness to act to avoid future climate change damage for all monotonic increasing $\psi(T)$ than will the policymaker under their prior beliefs. But, while we will consider this condition below, it is often overly restrictive. Therefore, we concentrate instead on what we define as the policymaker having a"low prior"; $E^{f^c}[\psi(T)] > E^f[\psi(T)]$ for a given damage function $D(T)$. Equivalently, we can say that the policymaker has a "low prior" if the willingness to act of the experts is greater than the willingness to act of the policymaker under their prior beliefs for a given, specific, damage function on which all parties agree.

From the definition of $\psi(T)$, we can write $D(T) = 1 - \exp(-\psi(T))$. We will primarily consider damage functions of the form $\psi(T) = \theta_k T^k$ for $\theta_k > 0$ and $k > 1$; results for an alternate form of damage function are available upon request from the authors. These functions are increasing and convex for all $T > 0$ and includes $D(T) = 1 - \exp\left(-\theta T^2\right)$ with $\theta = \theta_2$. This exponential quadratic specification has previously been used widely to represent climate change damage and therefore is particularly relevant for the problem at hand (Freeman et al., 2015; Pindyck, 2013; Pindyck, 2012; Weitzman, 2009). This damage function is used in the baseline calibrations in the body of the paper, when $\psi(T) = \theta T^2$ and p/y_0 is monotonic increasing in $E[T^2]$ for fixed θ.

Appendix B Bayesian updating of beliefs

The main theoretical results are new and based on the model of Morris (1974), who proves that, for some uncertain quantity, x, the relationship between (i) the prior distribution of the policymaker (using our terminology), $f(x|\Omega)$, based on their prior information Ω; (ii) the distribution of the experts, $f^c(x|\Omega_c)$, based on full scientific information Ω_c; and (iii) the posterior of the policymaker, $g(x|\Omega, f^c)$ after hearing the opinion of the experts, is given by:

$$g(x|\Omega, f^c) \propto L(f^c|x, \Omega) f(x|\Omega), \tag{3}$$

where $L(f^c|x, \Omega)$ is the likelihood function associated with the experts' information.

Unfortunately this model is "frustratingly difficult to apply" (Clemen and Winkler, 1999, p.190) because of the problem with assessing the likelihood function. However, as shown originally by Morris (1977), under five assumptions about the experts' assessment, $f^c(x|\Omega_c)$, this problem can be significantly simplified: (i) that $f^c(x|\Omega_c)$ is normally distributed; (ii) that $f^c(x|\Omega_c)$ is "invariant to scale": the precision of the experts' forecast, parameterized through the variance of $f^c(x|\Omega_c)$, does not, on its own, reveal information about the true value of x; (iii) that $f^c(x|\Omega_c)$ is "invariant to shift": if x suddenly changes to $x + \Delta$, then the mean of $f^c(x|\Omega_c)$ would also adjust by Δ; (iv) that the experts are perceived by the policymaker to be "accurate probability assessors" and so $f^c(x|\Omega_c)$ does not require calibration as technically described in Morris (1977): the policymaker accepts the experts' own assessment of the properties of their forecast error; (v) the experts' forecast error (the difference between the realization of x and the mean of $f^c(x|\Omega)$) is independent of the prior error of the policymaker. Under these assumptions, Morris (1977) proves that $L(f^c|x,\Omega) \equiv f^c(x|\Omega_c)$; the likelihood function $L(f^c|x,\Omega)$ is equal to the expert pdf and therefore directly observable from communication about the scientific consensus. In this case, equation (3) becomes:

$$g(x|\Omega, f^c) \propto f^c(x|\Omega_c) f(x|\Omega). \tag{4}$$

Under the Gaussian likelihood function, a normal distribution for the prior $f(x|\Omega)$ is conjugate, implying that $g(x|\Omega, f^c)$ is also normally distributed. This has led to the normal-normal model for $f^c(x|\Omega_c)$ and $f(x|\Omega)$ being the standard in the literature (e.g., Jacobs, 1995; Clemen and Winkler, 1985; Winkler, 1981). In other cases it is necessary to undertake some form of transformation of the underlying variable to convert it into a Gaussian distribution (Clemen and Winkler, 1999); this procedure is followed here.

Within this setting, the IPCC reports might be viewed as a "composite expert". In this case, we can imagine that there are $n \in \{1, ...N\}$ experts, each with professional assessment $f_n^c(x|\Omega_n^c) \sim N(\phi_n, \Sigma_n^2)$. Let Φ denote the vector $\Phi = \{\phi_1, ..., \phi_N\}$ and Ψ be an $N \times N$ matrix with elements $\Psi_{ij} = \varrho_{ij}\Sigma_i\Sigma_j$, where ϱ_{ij} is the correlation between the forecast errors of expert i and expert j. Then Winkler (1981) shows that the composite expert has a normally distributed opinion $f^c(x) \sim N(\phi, \Sigma^2)$ where:

$$\begin{aligned} \phi &= e'\Psi^{-1}\Phi / e'\Psi^{-1}e, \\ \Sigma^2 &= 1/e'\Psi^{-1}e, \end{aligned} \tag{5}$$

and e is an $N-$vector of ones.

B.1 Lognormal distributions

Assume that both the policymaker's prior and the consensus belief as summarized by the experts in the IPCC reports are lognormally distributed: $f(\ln(T)) \sim N(\mu, \sigma^2)$ and $f^c(\ln(T)) \sim N(\phi, \Sigma^2)$ respectively.[7] It is further assumed that this expert opinion is perfectly and non-strategically communicated to, and interpreted by, the policymaker. The policymaker's prior belief is that T has a mean value $E^f[T] = m$ and variance $Var^f[T] = s^2$, where, given the assumption of lognormality:

$$m = \exp(\mu + 0.5\sigma^2), \qquad s^2 = (\exp(\sigma^2) - 1)\exp(2\mu + \sigma^2). \tag{6}$$

Similarly the view of the experts is that T has a mean value $E^{f^c}[T] = M$ and variance $Var^{f^c}[T] = S^2$. The policymaker then creates a fully rational posterior probability density function for the logarithmic value of T, $g(\ln(T))$, through the application of Bayes' theorem. Following (e.g., Clemen and Winkler, 1985; Winker, 1981), $g(\ln(T)) \sim N(\mu', \sigma'^2)$ where:

$$\mu' = \frac{\mu/\sigma^2 + \phi/\Sigma^2}{1/\sigma^2 + 1/\Sigma^2}, \qquad \sigma'^2 = \frac{1}{1/\sigma^2 + 1/\Sigma^2}. \tag{7}$$

The posterior mean value of T, $E^g[T] = m'$ and variance $Var^g[T] = s'^2$ are related to μ' and σ'^2 in a way

[7]We now drop explicit notational reference to the Ω-relevant information, although this remains implicit in the discussion.

that is analogous to equation (6). We now consider five separate conditions and the relationship between them.

- C1 That the expert testimony first order stochastic dominates the prior belief of the policymaker; $f^c(T) \succ_{FSD} f(T)$. This is equivalent to $F^c(\tau) \leq F(\tau)$ for all τ, with the inequality being strict for at least one τ, where $F^c(\tau)$ and $F(\tau)$ denote the cumulative distribution functions of the experts' opinion and policymaker's prior beliefs respectively. For any τ, the experts assign a higher probability to $T > \tau$ than the policymaker under their prior beliefs. The necessary and sufficient conditions for this under lognormality are $\phi - \mu > 0$ and $\sigma - \Sigma = 0$ (Levy, 1973).
- C2 That the experts have a higher mean estimate of T than the policymaker under their prior; $M > m$. This is equivalent to $\phi - \mu > 0.5\left(\sigma^2 - \Sigma^2\right)$. Note that C1 $\Rightarrow$ C2 because, if $\sigma = \Sigma$ as required by C1, then C2 requires $\phi - \mu > 0$ which is identical to the other constraint in C1. The sufficiency of C1 for C2 also follows as a consequence of the property of first order stochastic dominance that $f^c(T) \succ_{FSD} f(T)$ directly implies that $E^{f^c}[T] > E^f[T]$. However C2 $\nRightarrow$ C1 both because C2 does not require $\sigma = \Sigma$ and because the sign of $\sigma^2 - \Sigma^2$ is indeterminate.
- C3 That the policymaker has a "low prior". This requires $E^{f^c}[\psi(T)] > E^f[\psi(T)]$, or, equivalently, $E^{f^c}\left[T^k\right] > E^f\left[T^k\right]$. With T being lognormally distributed, which has well-documented closed form solutions for its non-central moments, this is equivalent to $\exp\left(k\phi + 0.5k^2\Sigma^2\right) > \exp\left(k\mu + 0.5k^2\sigma^2\right)$, or $\phi - \mu > 0.5k\left(\sigma^2 - \Sigma^2\right)$. Analogous to the previous argument, C1 $\Rightarrow$ C3 but C3 $\nRightarrow$ C1. The sufficiency of C1 for C3 also follows from the properties of first order stochastic dominance and the fact that T^k is monotonic increasing, implying that $E^{f^c}[\psi(T)] > E^f[\psi(T)]$ for all monotonic increasing $\psi(T)$. By contrast C2 $\nRightarrow$ C3 and C3 $\nRightarrow$ C2 because $k > 1$ yet the sign of $\sigma^2 - \Sigma^2$ is indeterminate.
- C4 That the information being conveyed by the experts increases the mean estimate of the policymaker; $m' > m$. This condition holds if and only if $\mu' - \mu > 0.5\left(\sigma^2 - \sigma'^2\right)$. Substituting for μ', σ'^2 from equation (7) and simplifying shows that this inequality is equivalent to $\phi - \mu > 0.5\sigma^2$. Note now that C1 $\nRightarrow$ C4 as $0.5\sigma^2$ is positive and, as usual, C4 $\nRightarrow$ C1. As $\sigma^2 > \sigma^2 - \Sigma^2$, C2 $\nRightarrow$ C4 but C4 $\Rightarrow$ C2. Similarly, C3 $\nRightarrow$ C4 and C4 $\nRightarrow$ C3 because $k > 1$.
- C5 That, on reading an IPCC WG1 report, the policymaker increases their willingness to act to prevent climate change. Analogously to C3, this will occur if and only if $\mu' - \mu > 0.5k\left(\sigma^2 - \sigma'^2\right)$. Substituting for μ', σ'^2 from equation (7) and simplifying shows that this inequality is equivalent to $\phi - \mu > 0.5k\sigma^2$. Now C1 $\nRightarrow$ C5 as σ^2 is positive and, again, C5 $\nRightarrow$ C1. As $\sigma^2 > \sigma^2 - \Sigma^2$, C2 and C3 $\nRightarrow$ C5 but C5 $\Rightarrow$ C2, while C5 $\Rightarrow$ C3. Finally C4 $\nRightarrow$ C5 but C5 $\Rightarrow$ C4 because $k > 1$.

The necessary and sufficient relationships between the five conditions is summarized in Table 1. No condition is necessary and sufficient for any of the others, meaning that these are all clearly distinct. The inequalities for C4 and C5 are both of the form $\phi - \mu > 0.5\kappa\sigma^2$, with $\kappa = 1$ for C4 and $\kappa = k > 1$ for C5. For C4, given the properties of lognormality, this is equivalent to the observation that the median consensus estimate of T must be greater than the policymaker's mean prior estimate. The final inequality with $k = 2$ for C5, $\phi > \mu + \sigma^2$, is the one used in the Main.

The equivalent inequalities using the moments of T, with $k = 2$ for C3 and C5, are:

	C1	C2	C3	C4	C5
C1		$\Rightarrow$	$\Rightarrow$	$\not\Rightarrow$	$\not\Rightarrow$
C2	$\not\Rightarrow$		$\not\Rightarrow$	$\not\Rightarrow$	$\not\Rightarrow$
C3	$\not\Rightarrow$	$\not\Rightarrow$		$\not\Rightarrow$	$\not\Rightarrow$
C4	$\not\Rightarrow$	$\Rightarrow$	$\not\Rightarrow$		$\not\Rightarrow$
C5	$\not\Rightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	

Table 1: This table summarizes the necessary and sufficient relationships between the five conditions. The relationship has the condition in the first column on the left-hand side, and the condition in the top row on the right-hand side. The $\not\Rightarrow$ in the last column of the first row below the midrule should therefore be read as "C1 $\not\Rightarrow$ C5".

$$
\begin{array}{lll}
\text{C1} & \phi-\mu>0 \text{ and } \sigma-\Sigma=0 & \iff m<M \text{ and } s=mS/M, \\
\text{C2} & \phi-\mu>0.5\left(\sigma^2-\Sigma^2\right) & \iff m<M, \\
\text{C3 } (k=2) & \phi-\mu>\sigma^2-\Sigma^2 & \iff m^2<M^2+S^2-s^2, \\
\text{C4} & \phi-\mu>0.5\sigma^2 & \iff m^2<M^4\left(M^2+S^2\right)^{-1}, \\
\text{C5 } (k=2) & \phi-\mu>\sigma^2 & \iff m^2<M^4\left(M^2+S^2\right)^{-1}-s^2.
\end{array}
$$

Proof. Rearranging equation (6) gives,

$$\mu=\ln\left(\frac{m^2}{\sqrt{m^2+s^2}}\right), \qquad \sigma^2=\ln\left(\frac{m^2+s^2}{m^2}\right), \tag{8}$$

with analogous expressions for ϕ,Σ^2 with m,s replaced by M,S. Therefore:

$$\phi-\mu=\ln\left(\frac{M^2\sqrt{m^2+s^2}}{m^2\sqrt{M^2+S^2}}\right), \qquad \sigma^2-\Sigma^2=\ln\left(\frac{M^2(m^2+s^2)}{m^2(M^2+S^2)}\right), \tag{9}$$

and from this it is useful to note that

$$\phi-\mu-\frac{1}{2}\left(\sigma^2-\Sigma^2\right)=\ln\left(\frac{M}{m}\right). \tag{10}$$

All results follow from this. For C1, $\sigma-\Sigma=0$ if and only if $(\sigma+\Sigma)(\sigma-\Sigma)=\sigma^2-\Sigma^2=0$. This, in turn, requires from equation (9) that $(M^2(m^2+s^2))/(m^2(M^2+S^2))=1$, or equivalently that $M^2s^2=m^2S^2$ and therefore that $s=mS/M$. That M must be greater than m for $\phi-\mu>0$ then follows immediately from equation (10). Equation (10) also leads immediately to the single condition required for C2. For C3 note from equation (9) that:

$$\phi-\mu-(\sigma^2-\Sigma^2)=\ln\left(\sqrt{\frac{M^2+S^2}{m^2+s^2}}\right). \tag{11}$$

For the left hand side to be positive, $(M^2+S^2)/(m^2+s^2)>1$, giving the condition for C3. For C4 and C5, from equations (8) and (9):

$$\phi-\mu-\frac{1}{2}\sigma^2=\ln\left(\frac{M^2}{m\sqrt{M^2+S^2}}\right), \qquad \phi-\mu-\sigma^2=\ln\left(\frac{M^2}{\sqrt{m^2+s^2}\sqrt{M^2+S^2}}\right). \tag{12}$$

In both cases, for the inequality on the left is positive if and only if the term in the logarithmic function is greater than one. These give the results for C4 and C5. QED.

Additional robustness analysis for inequalities C1-C5 to the specific underlying assumptions are available upon request from the authors. These include numerical results beyond the single example in the Main, alternative damage functions, as well as different distributions than lognormal for T (Gaussian and Gamma distributions).

The analysis is not extended to more general utility functions than the logarithmic. This is because it then becomes necessary to also model economic growth and its correlation with T (Freeman et al., 2015). In a survey of experts on intergenerational discounting (Drupp et al., 2018), the median and modal recommended values of the elasticity of marginal utility for long-term threats is one, supporting the use of logarithmic utility in this paper.

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