Beliefs, evidence, and climate action*

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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 increase their investment in clean energy by the evidence in AR6.

Keywords: Climate policy, Energy policy, Climate risk, Equilibrium climate sensitivity, Bayesian updating

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1. Introduction

The IPCC calls for strong and urgent near-term climate action, with "a rapidly closing window of opportunity to secure a liveable and sustainable future for all (very high confidence)" (IPCC,

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2023, C.1). Much of this action relates to changes to the energy system, focused on:

> "a substantial reduction in overall fossil fuel use, minimal use of unabated fossil fuels, and use of carbon capture and storage in the remaining fossil fuel systems; electricity systems that emit no net CO2; widespread electrification; alternative energy carriers in applications less amenable to electrification; energy conservation and efficiency; and greater integration across the energy system (high confidence)". (IPCC, 2023, C3.2)

Such clear, direct language is laudable. It is, though, debatable whether it works, with Bayes et al. (2023) noting that: "Several studies fail to find direct effects of communicating the scientific consensus on support for greater action to address climate change, especially when it comes to climate skeptics or Republicans." More specifically, "the evidence presented to-date is insufficient to definitively show a mediated causal path from exposure to the scientific consensus message to support for pro-climate actions" (Bayes et al., 2023, p.17).

In this paper, we formally evaluate whether the scientific information contained in the IPCC's reports is likely to increase a mildly skeptical policymaker's willingness to act on climate, for example by putting greater resources behind the green energy transition. We focus our analysis in two ways. First, we consider policymakers who, despite being skeptical, are nevertheless accuracy-motivated (Druckman and McGrath, 2019). We, thus, assume that policymakers evaluate this 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. Second, we restrict our analysis only to the strength of the IPCC's statements concerning Equilibrium Climate Sensitivity (ECS) in their Fifth Assessment Report (AR5) (IPCC, 2013) and Sixth Assessment Report (AR6) (IPCC, 2021).

We make two contributions. First, we show that the policy impact of the IPCC's scientific statements will depend on *how* the accuracy-motivated policymaker incorporates this information into their beliefs. We consider two distinct possibilities: (i) the policymaker just accepts the IPCC's views as their own; or, instead (ii) they Bayesian update their prior beliefs about climate change based on what they read in this set of reports. The latter finds significant support in the literature, for example, "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). We show that under (i), AR5 has more power to drive policy action than AR6, while under (ii), AR6 is more powerful than AR5. We provide a simple explanation for why this superficially anomalous finding is, in fact, intuitively clear.

Second, it has been observed 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" (Deryugina and Shurchkov, 2016, p.1). The authors explain that the "lack of updating based on objective information in this context is consistent with a number of explanations, including strong priors, self-justification bias, selective attention, cultural norms, partisan bias, and information discounting" (Deryugina and Shurchkov, 2016, p.12).[1] Yet this behavior can also be explained fully rationally within the Bayesian updating model presented here. 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. Therefore, we show that the lack of policy in support of climate action that has previously been assigned to cognitive failures may, instead, reflect fully rational behavior.

2. Climate policy and Equilibrium Climate Sensitivity

Our focus is on whether the IPCC's statements concerning Equilibrium Climate Sensitivity are powerful enough to persuade a mildly skeptical, but well-intentioned, policymaker to put greater resources behind climate action. The 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 $1.5°C - 4.5°C$ (National Research Council, 1979). While the definition of what it means to be "likely" has become more precise over time (Bradley et al., 2017)—the Intergovernmental Panel on Climate Change (IPCC) now defines it as occurring with at least a 66% probability (Mastrandrea et al., 2010)—the range itself had remained steady at $1.5°C - 4.5°C$ for most of the IPCC's history (IPCC, 1990, 1995, 2001). The first exception came in the Fourth Assessment

[1]See also Wagner and Zeckhauser (2012) for other potential behavioral biases interfering in policymakers' ability to act upon new ECS or other climate information.

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).[2] 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, C.7).[3]

We consider how the ECS estimates in AR5 and AR6 may be assimilated by the policymaker, and how this then alters their willingness to put resources behind combating climate change. We measure this in two ways. In **Scenario 1**, following Freeman et al. (2015), we consider the maximum amount the policymaker would be prepared to pay to prevent all future climate change damages through, for example, investment in the clean energy transition that is needed to deliver net-zero greenhouse gas emissions. In **Scenario 2**, we theoretically extend Scenario 1 to consider the optimal amount that the policymaker would be prepared to pay to partially mitigate against future climate damage.

In contrast to much of the related previous literature (e.g., Hwang et al. (2017)), we recognize that those with the seniority to make substantive differences to climate policy are likely to only pay serious attention to the scientific consensus periodically, rather than continually keeping up-to-date with new findings as they are shared among the research community. We specifically consider how such senior policymakers will change their willingness to act if they are given *either* AR5 *or* AR6 to read for the first time.[4] Whichever single IPCC report a policymaker may be presented with, this presents significant new information about the ECS to them—even if the scientific community may have already anticipated many of the findings.

We test two separate hypotheses. For the first, we assume that the policymaker simply adopts the IPCC's judgements as their own. In this case, it has been proven under Scenario 1 that they

[2]Compared to AR5, other reported ranges in AR4 and earlier reports are difficult to interpret in likelihood terms, and therefore we restrict our analysis to the two most recent IPCC reports. For example, when consulting the IPCC AR4 statement and appropriate guidance note for interpreting likelihood terms, only few AR4 ECS numbers and ranges can be interpreted probabilistically compared to later reports.

[3]A prior expert elicitation by Zickfeld et al. (2010) concluded that "[t]en of the 14 experts estimated that the probability that equilibrium climate sensitivity exceeds $4.5°C$ is > 0.17". We here instead focus on how synthesis reports like Sherwood et al. (2020)'s are transmitted through the IPCC process.

[4]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. There are two reasons behind this choice. First, we deem the overlap of information in the two reports as too great to be able to clearly identify the new signal from AR6 relative to AR5. Second, and relatedly, the core assumption is that the forecasting error of the policymaker and the scientific consensus are uncorrelated with each other. Once the policymaker has incorporated AR5 into their beliefs, this assumption will be violated when they read AR6. One would either need to orthogonalize the information in AR6 to that known to the policymaker, or account for the correlation between the errors. Empirically, we cannot isolate these effects to pin down the direction of the bias.

would interpret the AR5 widening of the range compared to the previous AR4 report 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). This now 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. This forms the basis for our Hypothesis 1 under both Scenario 1 and Scenario 2:

Hypothesis 1. *If the policymaker fully accepts the scientific opinion in a single IPCC report, then their willingness to act will be* lower *if they read AR6 rather than AR5 for both Scenario 1 and Scenario 2.*

Our primary contributions relate to our second hypothesis. These come from recognizing that policymakers who read either AR5 or AR6 have prior beliefs about the ECS. Under such circumstances, they apply Bayes' Theorem rationally and accurately based on the scientists' own assessment of the remaining uncertainties surrounding the ECS.[5] We consider a policymaker who initially has a willingness to act below that would be justified by either AR5 or AR6. This policymaker is said to have a 'low prior'—an assumption which appears consistent with existing policy (Drupp et al., 2024). We examine the conditions under which such an accuracy-motivated, low-prior Bayesian policymaker will then change their willingness to act due to the IPCC updating its ECS range. Now the narrowing of the range in AR6 compared to AR5 is somewhat offset by the fact that the policymaker will more weakly incorporate the scientific consensus into their own opinions under AR5 than AR6—we explain why in more detail below. As a consequence, we may now expect AR6 to have the greater power to convince the policymaker to take greater action. This forms the basis for our second hypothesis under both Scenario 1 and Scenario 2.

Hypothesis 2. *Consider a policymaker with a low prior. If this policymaker Bayesian updates their views in an accuracy-motivated way based on the scientific consensus, then reading AR6 rather than AR5 has greater power to increase their willingness to act for both Scenario 1 and Scenario 2.*

Our main results prove that both Hypothesis 1 and Hypothesis 2 are true, even though they

[5]This contrasts with, for instance, Augenblick et al. (2024), who examine how people apply Bayes' Theorem imprecisely when updating their views. Our work echoes Hwang et al. (2017), who also considers how Bayesian learning affects climate and energy policy choices, with a primary focus on the optimal timing of irreversible investment.

superficially appear to be contradictory. Therefore, if policymakers with low priors rationally and accurately Bayesian update their views, AR6 has strictly greater power than AR5 to increase such a policymaker's willingness to act on climate.

3. Policy response to new scientific information

Under a set of plausible assumptions, the willingness to act to 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 the maximum amount that a policymaker should be prepared to pay to fully prevent future climate change damage is monotonically increasing in $E[T^2] = (E[T])^2 + \text{Var}[T]$ (Freeman et al., 2015, see also Appendix A). This is our Scenario 1. As expected, this captures both the magnitude of the expected future level of climate change, and how uncertain we are about this central forecast. In Appendix B we extend this result to Scenario 2, where the policymaker is determining the optimal amount to spend to partially prevent climate change damage (the internal solution). Again, it is shown that, under plausible assumptions about the relationship between future climate damages for given ECS and prevention, this value is monotonic increasing in $E[T^2]$. Since $E[T^2]$ drives the willingness to act under both Scenario 1 and Scenario 2, we no longer need to distinguish between them.

The central purpose of this paper is to consider how an accuracy-motivated policymaker will re-evaluate their willingness to act when presented with scientific consensus evidence on the ECS presented in *either* AR5 *or* AR6.[6] Since this is determined through $E[T^2]$, it is necessary to consider how this mathematical expectation changes based on this new information. This task requires us to clearly differentiate between five distinct probability density functions (PDFs), which we describe

[6] 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, may also heavily impact the Social Cost of Carbon (Moore et al., 2024; Hänsel et al., 2020; Rennert et al., 2022) and, thus, policymakers' willingness to act.

below. If $f_j(T)$ for $j \in \{1, \dots 5\}$ is used to denote each of these PDFs, then we introduce the notation $E_j[T^2]$ in the main body of the paper to mean $E[T^2]$ when calculated under PDF j, which we assume throughout is well-defined:

$$E_j[T^2] \stackrel{\text{def}}{=} \int_0^\infty T^2 f_j(T) dT.$$

3.1. The scientific evidence (PDF1, PDF2)

The information contained in the IPCC reports does not give a single value for the ECS. Instead, it gives ranges of possible values. For example,

> "The AR6 best estimate of ECS is 3°C, the *likely* range is 2.5°C to 4°C and the *very likely* range is 2°C to 5°C. There is a high level of agreement among the four main lines of evidence listed above (Figure TS.16b), and altogether it is *virtually certain* that ECS is larger than 1.5°C, but currently it is not possible to rule out ECS values above 5°C". (Working Group 1, Section TS.3.2.1).

Here, terms such as *likely* and *very likely* are formalized as likelihoods in a way that is consistent across AR5 and AR6; see Table 1:

[Insert Table 1 around here.]

We infer probability density functions that are broadly consistent with such statements to capture this consensus scientific opinion. Since these statements differ between AR5 and AR6, we use different PDFs to capture the information in each. We denote these by "PDF1" ($j = 1$) for the information in AR5, and "PDF2" ($j = 2$) for the information in AR6. For Hypothesis 1, the policymaker takes the expert consensus in the IPCC report they read completely at face value. Therefore their opinion is captured by PDF1 if they are given AR5 to read, and PDF2 if they are given AR6 to read instead. Stated mathematically, Hypothesis 1 is therefore equivalent to saying that $E[T^2]$ is greater when calculated under PDF1 than PDF2;

$$\text{Hypothesis 1:} \qquad E_2[T^2] < E_1[T^2].$$

3.2. The prior beliefs of the policymaker before reading an IPCC report (PDF3)

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. Instead, they have initial beliefs about the true value of this parameter. Rather than having certainty reflected in a single value estimate, they instead recognize that there is a range of possible values that the ECS might take and to which they assign their own probabilities. This initial view — the "prior distribution" in Bayesian terms — can be captured by its own probability density function ("PDF3"; $j = 3$). Our focus is specifically on policymakers with a "low prior" — that the policymaker's prior willingness to act is below that justified by either AR5 or AR6. We can now mathematically define this as $E[T^2]$ being lower when calculated under PDF3 than under both PDF1 and PDF2;

$$\text{Definition of "low prior":} \qquad E_3[T^2] < \min[E_1[T^2], E_2[T^2]].$$

3.3. The updated beliefs of the policymaker after reading an IPCC report (PDF4, PDF5)

After reading the IPCC report, for Hypothesis 2, the policymaker rationally and accurately uses Bayes Theorem to update their views. Their revised views are then reflected in a new, "posterior", probability density function. If they read AR5 then this posterior distribution is called "PDF4" ($j = 4$), while "PDF5" ($j = 5$) is the posterior distribution if the policymaker reads AR6 instead. Hypothesis 2 can now be stated mathematically that if $E_4[T^2]$ is greater than $E_3[T^2]$ — that is, AR5 causes the policy maker to want to take greater action — then this is sufficient to ensure that $E_5[T^2]$ will also be greater than $E_3[T^2]$ because AR6 is more powerful to drive change. However, this sufficiency condition does not work in the other direction:

$$\text{Hypothesis 2:} \qquad E_4[T^2] > E_3[T^2] \underset{\not\Leftarrow}{\Rightarrow} E_5[T^2] > E_3[T^2].$$

What is crucial for Hypothesis 2 is the way in which the policymaker updates their beliefs under Bayes Theorem. As is shown in Appendix C, the mean of their updated ("posterior") distribution is a weighted average of the mean of their initial ("prior") distribution and the mean of the scientific consensus. The weightings on each are positive and they sum to one. The key characteristic of these weightings is that the more certain the scientific community is about the true value of the ECS, reflected in PDF1, PDF2 having low standard deviations, the more strongly the mean of the posterior distribution will align with the scientific consensus. Under Bayesian updating, the greater confidence that scientists express in their central estimate of T, the more closely the policymaker will align with that opinion.

However, when we consider the *precision*—the reciprocal of the variance—of the posterior distribution, this is just the sum of the precisions of the prior distribution (PDF3) and the scientific consensus (PDF1 or PDF2). Therefore, the variance of the posterior distribution will always be lower than the variances of both the prior distribution and the scientific consensus. Moreover, the more precise the evidence is, the lower the variance of the posterior distribution. This offsets the impact of the alignment of the mean with the scientific consensus when considering the overall effect on $E[T^2] = (E[T])^2 + \mathrm{Var}[T]$. It is the trade-off between these mean and variance effects that drive the results of our Bayesian analysis.[7]

4. The scientific evidence and the policymaker's prior

To establish and quantify our results, we must first parameterize PDF1, PDF2 and PDF3 and then, in Section 5, use Bayesian updating under expert information to derive PDF4 and PDF5.

4.1. The scientific evidence

In this section, we follow Sherwood et al. (2020); Wagner and Weitzman (2015, 2018); Weitzman (2007, 2009) in assuming that the scientific consensus for T is lognormally distributed. In this case, we need to estimate values of the mean and standard deviation of this distribution that broadly match the likelihood statements in AR5 and AR6. We summarize our parameterizations in Table 2.

[Insert Table 2 around here.]

PDF1. We parameterize the relevant section of AR5 (IPCC, 2013, Section TS5.3) 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

[7] We here assume that the forecasting error of the policymaker and the scientific consensus are uncorrelated with each other.

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 $T > 6°C$.[8]

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; Bradley et al., 2017).[9]

4.2. The policymaker's prior

PDF3. In contrast to the scientific consensus, we do not formally calibrate the policymaker's prior. Since each individual policymaker will have their own personal views that they are unlikely to express in formal likelihood terms, such a calibration exercise is not feasible. Instead, we give an illustrative example of a policymaker whose prior position makes them mildly skeptical regarding the need to align resources with more ambitious climate action. 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 stress that our main results do not depend on the calibration of PDF3.

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 $\phi_{AR5} + \Sigma^2_{AR5} = 1.328$

[8] Specifically, 66.0%, 4.1%, and 8.4%, respectively.
[9] Specifically, 67.4%, 94.4%, 0.1% and 96.8%, respectively.

$> 1.223 = \phi_{AR6} + \Sigma^2_{AR6}$, $E_1[T^2] > E_2[T^2]$. 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 confirms our Hypothesis 1. 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).

[Insert Figure 1 around here.]

5. 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 C.

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 C, 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.[10] In addition, while expert uncertainty around $\ln(T)$ (as captured by Σ in PDF1 and PDF2) will directly influence the policymaker's 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 increase their mean estimate of the ECS, or be more willing to act, after reading an IPCC report; conditions (ii) and (iii) are not functions of Σ. This is because, as explained above, 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, $E[T]$ increases 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. In Appendix D, we present a calibration of this result for the internal solution from Scenario 2. In this case (see Table 4), under AR6, the optimal amount the policymaker would wish to spend to reduce the impact of climate change increases from 3.22% of current consumption under the prior to 4.66% under the Bayesian posterior; an economically significant rise. Under AR5, the optimal spend declines to 2.87%. This quantifies our main result.

This finding appears, at least superficially, somewhat paradoxical given our first result. More generally, as $\phi_{AR6} > \phi_{AR5}$, AR6 has strictly more power to persuade the policymaker to increase

[10]In Appendix C 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.

their willingness to pay to prevent future climate damage than AR5 would if the policymaker is presented with only one of these reports. This confirms our Hypothesis 2.

In Figure 2, we present, for different values of the standard deviation of the policymaker's prior on T, s, the upper bound on the policymaker's mean, m, to make them more willing to take climate action after reading an IPCC report. As the bound for AR6 is always above the bound for AR5, this again illustrates that AR6 is more powerful than AR5 under Bayesian updating. The gap between the two lines is relatively substantial (of the order of half a degree centigrade) for all values of s, but the upper bound for both AR5 and AR6 declines as s increases. Policymakers are more easily persuaded to take action if there is high uncertainty in their prior.

[Insert Figure 2 around here.]

6. Conclusion

The willingness to act on climate change increases both with the expected ECS value and with its uncertainty. Because the spread of ECS estimates is much narrower in AR6 than AR5, policymakers' willingness to act goes down from AR5 to AR6, when reading either report in isolation (Hypothesis 1). But this ignores policymakers' priors. With Bayesian updating, we show here that the ECS estimates in AR6 have strictly greater power to persuade the policymaker to change their policy views in favor of greater willingness to act on climate policies (Hypothesis 2).

In Appendix E, we show that our broad conclusions are robust to other distributions for ECS (T) beyond the lognormal. 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, $E[T]$, is likely (though not certain) to increase, while Bayesian posteriors will be more precise than their priors. Therefore, $E[T^2] = (E[T])^2 + \text{Var}[T]$ generally has offsetting terms that support Hypothesis 2.

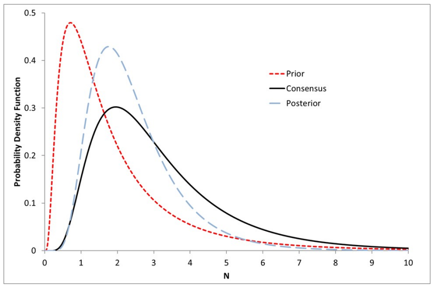
This conclusion speaks to two related areas of the literature. First, IPCC updates matter, both in substance and in the way the results are communicated. That goes especially for how the IPCC communicates uncertainty ranges and confidence intervals (Kopp et al., 2023; Bradley et al., 2017). Yet those moderately hesitant to embrace climate-scientific results are often unpersuaded to take further action, despite sometimes being more willing to ‘believe’ in climate change after reading scientific evidence (Lewandowsky, 2021; Kahan, 2016; Bolsen and Druckman, 2016; Deryugina and Shurchkov, 2016). While this work relates to members of the public, and not policymakers directly, our results provide a formal framework that potentially reconciles these findings, emphasizing the need to consider readers’ priors—picking people up where they are. None of that means watering down information, but it does mean carefully thinking about how uncertainty is presented, especially in public communication (Wagner, 2022).

Term	Associated likelihood
Virtually certain	99% – 100%
Extremely likely	95% – 100%
Very likely	90% – 100%
Likely	66% – 100%
More likely than not	50% – 100%
About as likely as not	33% – 66%
Unlikely	0% – 33%
Very unlikely	0% – 10%
Extremely unlikely	0% – 5%
Exceptionally unlikely	0% - 1%

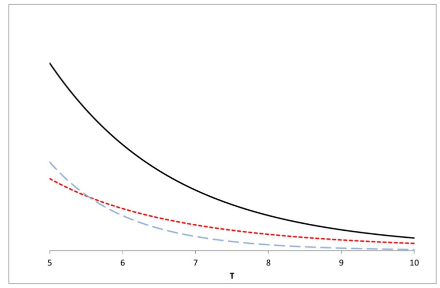
Table 1: The IPCC guidance note for interpreting likelihood terms in AR5 and AR6. See Mastrandrea et al. (2011).

IPCC statement	Inferred statistical properties of ECS from IPCC statement		Statistical properties of PDF1 for AR5 and PDF2 for AR6	
"(The) ECS is positive, *likely* in the range 1.5°C to 4.5°C with high confidence, *extremely unlikely* less than 1°C (high confidence) and *very unlikely* greater than 6°C (medium confidence)." (AR5 Working Group 1, Section TS5.4).	Prob $1.5 < T < 4.5$ Prob $T < 6$ Prob $T > 1$	66% 90% 95%	Prob $1.5 < T < 4.5$ Prob $T < 6$ Prob $T > 1$	66.0% 91.6% 95.6%
"The AR6 best estimate of ECS is 3°C, the *likely* range is 2.5°C to 4°C and the *very likely* range is 2°C to 5°C. There is a high level of agreement among the four main lines of evidence listed above (Figure TS.16b), and altogether it is *virtually certain* that ECS is larger than 1.5°C, but currently it is not possible to rule out ECS values above 5°C". (AR6 Working Group 1, Section TS.3.2.1).	Median Prob $2.5 < T < 4$ Prob $2 < T < 5$ Prob $T > 1.5$	3 66% 90% 99%	Median Prob $2.5 < T < 4$ Prob $2 < T < 5$ Prob $T > 1.5$	3.21 67.4% 94.4% 99.9%

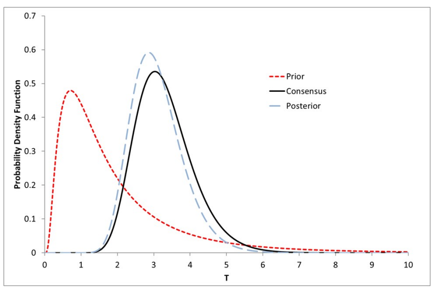
Table 2: The first column gives the wording in the IPCC AR5 and AR6 reports summarizing the scientific consensus on the ECS. In the second column, we interpret these statements statistically using the definitions in Table 1. The third column gives information about PDF1 and PDF2, which approximate the IPCC statements for AR5 and AR6 respectively. In both cases it is assumed that $\ln(T) \sim N(\phi, \Sigma^2)$, with $\phi_{AR5} = 0.9983, \Sigma_{AR5} = 0.5742$ for PDF1. For PDF2, $\phi_{AR6} = 1.1654, \Sigma_{AR6} = 0.2390$.



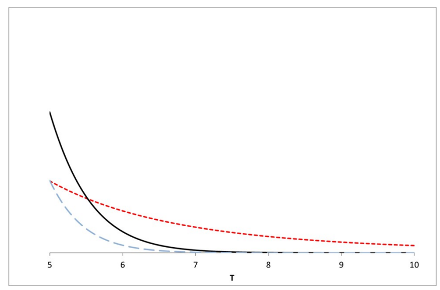
(a)



(b)



(c)



(d)

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.

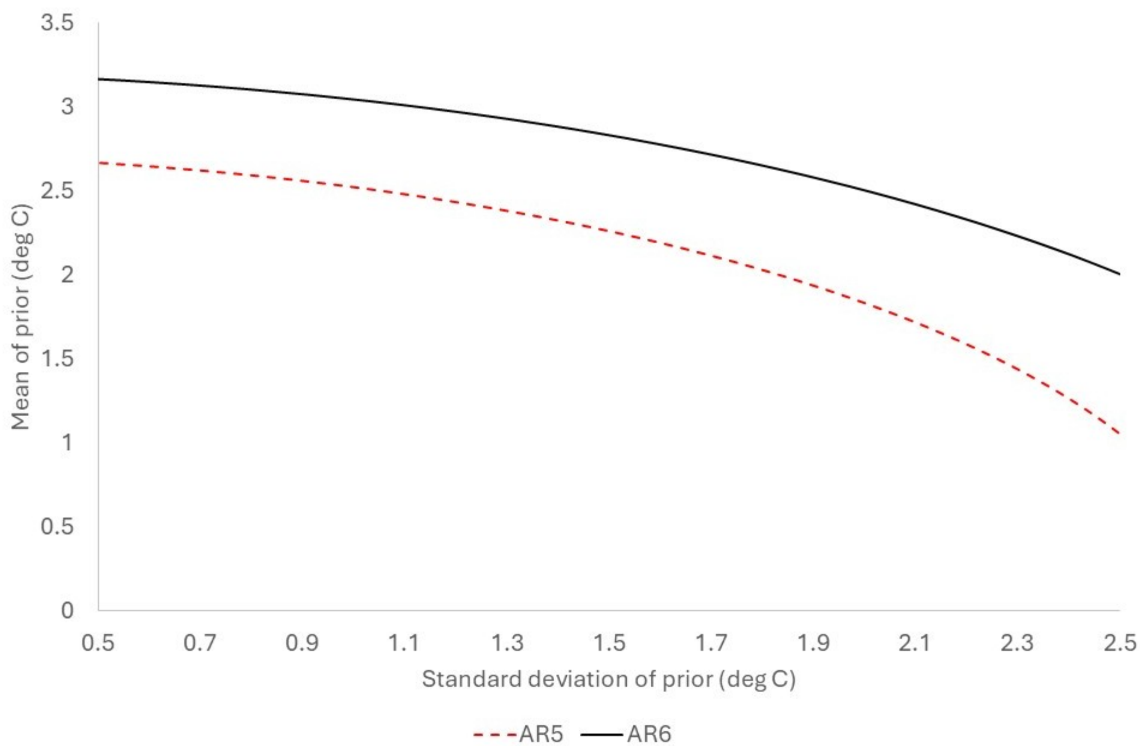


Figure 2: Upper bound on the policymaker's mean value of T that would lead to increased willingness to act based on reading either AR5 or AR6. Note that the bound for AR6 is above AR5's for all values of the standard deviation of the policymaker's prior, confirming that AR6 has the greater power to affect policy action under Bayesian updating.

Appendices

Appendix A. Scenario 1

In this Appendix, 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 $E[T^2]$.

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 updates their beliefs. 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.

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 $\rho \geq 0$ 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 $E[\psi(T)]$. In our Bayesian setting, 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 include $D(T) = 1 - \exp\left(-\theta T^2\right)$ 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, 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. Scenario 2

We now extend the analysis in Appendix A to consider internal solutions. In Scenario 1, consumption in the future is given by $\exp(-\theta T^2)y_t^*$ when climate change is not prevented, and y_t^* if it is fully prevented. For an internal level of spend, $v < y_0$, we can generalize this to $\exp(-\theta(v)T^2)y_t^*$, with $\theta(v)$ being strictly decreasing and weakly convex in v: $d\theta(v)/dv < 0, d^2\theta(v)/dv^2 \geq 0$. Notice that lower values of $\theta(v)$ correspond to lower future climate damages for given T^2, so the more we spend on prevention, the less effect the ECS will have on damages, with weakly diminishing marginal returns to scale on such investment. This broadly nests the model in the main body where $\theta(p) = 0$ and $\theta(0) = \theta$ but where no other point is specified. Following equation (1), the policymaker will look to maximize the welfare function W, where:

$$\begin{aligned} W &= \ln(y_0 - v) + e^{-\rho t}E[\ln(\exp(-\theta(v)T^2)y_t^*)] \\ &= \ln(y_0 - v) - e^{-\rho t}\theta(v)E[T^2] + e^{-\rho t}E[\ln(y_t^*)]. \end{aligned} \tag{3}$$

To find the properties of the turning points of W with respect to v, take the first and second derivatives:

$$
\begin{aligned}
\frac{dW}{dv} &= \frac{-1}{y_0 - v} - e^{-\rho t} E[T^2] \frac{d\theta(v)}{dv} \\
\frac{d^2W}{dv^2} &= \frac{-1}{(y_0 - v)^2} - e^{-\rho t} E[T^2] \frac{d^2\theta(v)}{dv^2}.
\end{aligned}
$$

The first derivative is not definitively of fixed sign because $d\theta(v)/dv < 0$. By contrast, the sign of the second derivative is always negative because $d^2\theta(v)/dv^2 \geq 0$; $W(v)$ is concave in v. Therefore any turning point of W with respect to v will be a maximum. The value of v that equates to this maximum is set when the first derivative of W with respect to v equals zero:

$$
\begin{aligned}
0 &= \frac{-1}{y_0 - v} - e^{-\rho t} E[T^2] \frac{d\theta(v)}{dv} \\
\Rightarrow \quad v &= y_0 + e^{\rho t} \left(E[T^2] \frac{d\theta(v)}{dv} \right)^{-1}.
\end{aligned} \tag{4}
$$

To understand the relationship between this optimal level of spend, v, and $E[T^2]$, take the first derivative of both sides of this equation with respect to $E[T^2]$:

$$
\begin{aligned}
\frac{dv}{dE[T^2]} &= \frac{-e^{\rho t}}{E[T^2]^2} \left(\frac{d\theta(v)}{dv} \right)^{-1} + \frac{e^{\rho t}}{E[T^2]} \frac{d}{dv} \left(\frac{d\theta(v)}{dv} \right)^{-1} \frac{dv}{dE[T^2]} \\
&= \frac{-e^{\rho t}}{E[T^2]^2} \left(\frac{d\theta(v)}{dv} \right)^{-1} - \frac{e^{\rho t}}{E[T^2]} \left(\frac{d\theta(v)}{dv} \right)^{-2} \frac{d^2\theta(v)}{dv^2} \frac{dv}{dE[T^2]} \\
&= \frac{-e^{\rho t}}{E[T^2]^2} \left(\frac{d\theta(v)}{dv} \right)^{-1} \left(1 + \frac{e^{\rho t}}{E[T^2]} \left(\frac{d\theta(v)}{dv} \right)^{-2} \frac{d^2\theta(v)}{dv^2} \right)^{-1} \\
&= -\frac{1}{E[T^2]} \frac{d\theta(v)}{dv} \left(e^{-\rho t} E[T^2] \left(\frac{d\theta(v)}{dv} \right)^2 + \frac{d^2\theta(v)}{dv^2} \right)^{-1} \\
&> 0,
\end{aligned}
$$

where the third line follows by moving $dv/dE[T^2]$ to the left-hand side. This shows that the interior optimal spend level, v, when defined as such, is indeed monotonic increasing in $E[T^2]$ as required.

Appendix C. 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:

$$g\left(x|\Omega, f^c\right) \propto L\left(f^c|x, \Omega\right) f\left(x|\Omega\right), \tag{5}$$

where $L\left(f^c|x, \Omega\right)$ 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, $f^c\left(x|\Omega_c\right)$, this problem can be significantly simplified: (i) that $f^c\left(x|\Omega_c\right)$ is normally distributed; (ii) that $f^c\left(x|\Omega_c\right)$ is "invariant to scale": the precision of the experts' forecast, parameterized through the variance of $f^c\left(x|\Omega_c\right)$, does not, on its own, reveal information about the true value of x; (iii) that $f^c\left(x|\Omega_c\right)$ is "invariant to shift": if x suddenly changes to $x+\Delta$, then the mean of $f^c\left(x|\Omega_c\right)$ would also adjust by Δ; (iv) that the experts are perceived by the policymaker to be "accurate probability assessors" and so $f^c\left(x|\Omega_c\right)$ 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 $f^c\left(x|\Omega\right)$) is independent of the prior error of the policymaker. Under these assumptions, Morris (1977) proves that $L\left(f^c|x, \Omega\right) \equiv f^c\left(x|\Omega_c\right)$; the likelihood function $L\left(f^c|x, \Omega\right)$ is equal to the expert PDF and therefore directly observable from communication about the scientific consensus. In this case, equation (5) becomes:

$$g\left(x|\Omega, f^c\right) \propto f^c(x|\Omega_c) f\left(x|\Omega\right). \tag{6}$$

Under the Gaussian likelihood function, a normal distribution for the prior $f\left(x|\Omega\right)$ is conjugate, implying that $g\left(x|\Omega, f^c\right)$ is also normally distributed. This has led to the normal-normal model for $f^c\left(x|\Omega_c\right)$ and $f\left(x|\Omega\right)$ 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 $f_n^c\left(x|\Omega_n^c\right) \sim N\left(\phi_n, \Sigma_n^2\right)$. 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

$f^c(x) \sim N\left(\phi, \Sigma^2\right)$ where:

$$\begin{aligned} \phi &= e'\Psi^{-1}\Phi/e'\Psi^{-1}e, \\ \Sigma^2 &= 1/e'\Psi^{-1}e, \end{aligned} \tag{7}$$

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

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: $f(\ln(T)) \sim N\left(\mu, \sigma^2\right)$ and $f^c(\ln(T)) \sim N\left(\phi, \Sigma^2\right)$ respectively.[11] 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:

$$m = \exp\left(\mu + 0.5\sigma^2\right), \qquad s^2 = \left(\exp\left(\sigma^2\right) - 1\right)\exp\left(2\mu + \sigma^2\right). \tag{8}$$

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); Winkler (1981), $g(\ln(T)) \sim N(\mu', \sigma'^2)$ where:

$$\mu' = \frac{\mu/\sigma^2 + \phi/\Sigma^2}{1/\sigma^2 + 1/\Sigma^2}, \qquad \sigma'^2 = \frac{1}{1/\sigma^2 + 1/\Sigma^2}. \tag{9}$$

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 that is analogous to equation (8). 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

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

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 (9) 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 (9) 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 are summarized in Table

3. 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 body of the paper.

	C1	C2	C3	C4	C5
C1		$\Rightarrow$	$\Rightarrow$	$\nRightarrow$	$\nRightarrow$
C2	$\nRightarrow$		$\nRightarrow$	$\nRightarrow$	$\nRightarrow$
C3	$\nRightarrow$	$\nRightarrow$		$\nRightarrow$	$\nRightarrow$
C4	$\nRightarrow$	$\Rightarrow$	$\nRightarrow$		$\nRightarrow$
C5	$\nRightarrow$	$\Rightarrow$	$\Rightarrow$	$\Rightarrow$	

Table 3: 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 $\nRightarrow$ in the last column of the first row below the midrule should therefore be read as "C1 $\nRightarrow$ C5".

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

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

Proof. Rearranging equation (8) gives,

$$\mu = \ln\left(\frac{m^2}{\sqrt{m^2 + s^2}}\right), \qquad \sigma^2 = \ln\left(\frac{m^2 + s^2}{m^2}\right), \tag{10}$$

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

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

and from this it is useful to note that

$$\phi - \mu - \frac{1}{2}\left(\sigma^2 - \Sigma^2\right) = \ln\left(\frac{M}{m}\right). \tag{12}$$

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 (11) that $(M^2(m^2+s^2))/(m^2(M^2+S^2)) = 1$, or equivalently that $M^2 s^2 = m^2 S^2$ and therefore that $s = mS/M$. That M must be greater than m for $\phi - \mu > 0$ then follows immediately from equation (12). Equation (10) also leads immediately to the single condition required for C2. For C3 note from equation (11) that:

$$\phi - \mu - (\sigma^2 - \Sigma^2) = \ln\left(\sqrt{\frac{M^2+S^2}{m^2+s^2}}\right). \tag{13}$$

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 (10) and (11):

$$\phi - \mu - \frac{1}{2}\sigma^2 = \ln\left(\frac{M^2}{m\sqrt{M^2+S^2}}\right), \qquad \phi - \mu - \sigma^2 = \ln\left(\frac{M^2}{\sqrt{m^2+s^2}\sqrt{M^2+S^2}}\right). \tag{14}$$

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 body of the paper, 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.

Appendix D. Calibrating Scenario 2

To make the internal solution case more concrete, take a specific example. Assume that $\theta(v) = \theta\exp(-\zeta v)$ for a fixed $\zeta > 0$, which satisfies the property of being monotonic decreasing in v and convex; $d\theta(v)/dv = -\theta\zeta\exp(-\zeta v) < 0$, and $d^2\theta(v)/dv^2 = \theta\zeta^2\exp(-\zeta v) > 0$. Substituting into equation (4):

$$v = y_0 - \frac{e^{\rho t+\zeta v}}{\theta\zeta E[T^2]}.$$

Taking the first derivative with respect to $E[T^2]$:

$$\begin{aligned}
\frac{dv}{dE[T^2]} &= \frac{e^{\rho t+\zeta v}}{\theta\zeta E[T^2]^2} - \frac{\zeta e^{\rho t+\zeta v}}{\theta\zeta E[T^2]}\frac{dv}{dE[T^2]} \\
\Rightarrow \frac{dv}{dE[T^2]} &= \frac{e^{\rho t+\zeta v}}{\theta\zeta E[T^2]^2}\left(1+\frac{\zeta e^{\rho t+\zeta v}}{\theta\zeta E[T^2]}\right)^{-1} \\
&= \frac{e^{\rho t+\zeta v}}{\theta\zeta E[T^2]^2}\frac{\theta\zeta E[T^2]}{\theta\zeta E[T^2]+\zeta e^{\rho t+\zeta v}} \\
&= \frac{e^{\rho t+\zeta v}}{\zeta E[T^2](\theta E[T^2]+e^{\rho t+\zeta v})} > 0.
\end{aligned}$$

This confirms that the turning point is monotonic increasing in $E[T^2]$.

To calibrate this, assume that if $v = 0$ and $T = 4°C$, then consumption would drop by 20%, a number well within the range of estimates (Moore et al., 2024; IPCC, 2021, ECONOMIC.1). Then $\exp(-\theta 4^2) = 0.8$, or $\theta = -\ln(0.8)/16 = 0.01395$. Now assume that, if $y_0 = \$10,000$ per capita, and that spending $v = 500$ will halve the damages, then $\exp(-\theta(500)4^2) = 0.9$, or $\theta(500) = -\ln(0.9)/16$, or $\theta(500) = 0.006585$. Then $\zeta = -\ln(\theta(500)/\theta)/500 = 0.001501$. Set $\rho = 0$. Then, for the five probability density functions that form the basis for this paper, the optimal internal spend value of v is given in Table 4. This confirms that v increases for higher $E[T^2]$, and that AR6 gives a stronger call to action under Bayesian updating than does AR5.

Appendix E. Alternative distributions for *T*

Appendix E.1. Normally distributed climate change

Suppose that both the experts within the IPCC reports, and the policymaker under their prior, believe T to be normally distributed. In this case equation (9) can be applied directly with

Lognormal distribution	AR5 PDF1	AR6 PDF2	Prior PDF3	Post(AR5) PDF4	Post(AR6) PDF5
μ	0.9983	1.1654	0.3466	0.7882	1.1030
σ	0.5742	0.2390	0.8326	0.4727	0.2297
$E[T^2]$	14.2394	11.5310	8.0016	7.5632	10.0898
Optimal spend, v, as % y_0	6.81%	5.49%	3.22%	2.87%	4.66%

Table 4: This gives the optimal spend, v, as a proportion of initial income, y_0, for the five different probability functions in the body of the text when $y_0 = \$10,000$, $\theta(v) = \theta \exp(-\zeta v)$ with $\theta = 0.01395$ and $\zeta = 0.001501$.

m, M, s, S replacing $\mu, \phi, \sigma, \Sigma$ to give m' and s'. As $M > m$, it follows from equation (9) that:

$$m' = \frac{m/s^2 + M/S^2}{1/s^2 + 1/S^2} > \frac{m/s^2 + m/S^2}{1/s^2 + 1/S^2} = m. \tag{15}$$

and so, their expected value of T increases. In terms of the policymakers' willingness to take greater climate action, the following result holds:

Result for the normal distribution. Under the assumption that both the prior distribution of the policymaker and the distribution of expert opinion for T are both normally distributed:

- If $M^2 < S^2 + s^2 - S^4/(S^2 + s^2)$, then the policymaker will never increase their willingness to take more action on hearing the evidence, irrespective of the value of m.
- If $M^2 = S^2 + s^2 - S^4/(S^2 + s^2)$, then the policymaker will never be willing to take more action on hearing the evidence, although the willingness to act will be unchanged if and only if $m = MS^2/\left(2S^2 + s^2\right)$.
- If $M^2 > S^2 + s^2 - S^4/(S^2 + s^2)$, then the policymaker will take more action if m lies between the lower root and the upper root of the following quadratic equation:

$$\left(2S^2 + s^2\right) m^2 - \left(2MS^2\right) m + s^2 \left(S^2 + s^2 - M^2\right) = 0. \tag{16}$$

Proof. For the willingness to take action to remain unchanged, $m^2 + s^2 - m'^2 - s'^2 = 0$:

$$m^2 + s^2 - \left(\frac{m/s^2 + M/S^2}{1/s^2 + 1/S^2}\right)^2 - \frac{1}{1/s^2 + 1/S^2} = 0$$
$$\implies \left(\frac{2}{s^2S^2} + \frac{1}{S^4}\right)m^2 - \frac{2M}{s^2S^2}m + \frac{S^2 + s^2 - M^2}{S^4} = 0 \tag{17}$$

This is a standard quadratic of the form $am^2 + bm + c = 0$. There are no real roots to this quadratic equation in m if $b^2 - 4ac < 0$ which is equivalent to:

$$M^2 < S^2 + s^2 - \frac{S^4}{S^2 + s^2} \tag{18}$$

If this inequality holds, then the sign of $m^2 + s^2 - m'^2 - s'^2$ is constant for all m as the left-hand side of equation (17) never passes through zero. This sign can be determined by considering the case $m = 0$, which reveals that this equation is positive (indicating a reduced willingness to take action) if $M^2 < S^2 + s^2$. This condition must hold because of the stronger inequality in expression (18). Therefore, when there are no real solutions to the quadratic equation, the willingness to take action always decreases when the policymaker reads an IPCC report.

Next, note that the second derivative of the quadratic with respect to m is positive. This means that the function is upward $U-$shaped. The sign of $m^2 + s^2 - m'^2 - s'^2$ is therefore positive both above the upper root and below the lower root of the quadratic equation (or increasing on both sides of the single root when $b^2 - 4ac = 0$). The willingness to take action therefore only increases in the case when m lies between the two roots of the quadratic. This completes the proof. QED.

For AR5, $M = 3.2°C$ and $S = 2°C$, while for AR6, $M = 3.3°C$ and $S = 0.8°C$. In our baseline calibration of the policymaker's prior, when $s = 2°C$, $M^2 > S^2 + s^2 - S^4/(S^2 + s^2)$ in both cases. The two real roots of the quadratic equation are $2.439°C$ and $-0.306°C$ for AR5 and $-1.812°C$ and $2.613°C$ for AR6. The baseline case of $m = 2°C$ lies between the two roots in both cases, and so the policymaker would increase their willingness to take action. However, if $m = 2.5°C$, which lies above the upper bound of AR5 but below the upper bound of AR6, then, again, AR6 has stronger power.

The reason why the willingness to take action decreases if m is below the lower bound relates to two features of this analysis: first, that under a normal distribution, negative values of T have non-zero probabilities associated with them both by the expert and the policymaker's prior, meaning that both believe there is a possibility that increased CO_2 concentrations will reduce global average temperatures; second, that the damage function is quadratic in T, meaning that positive and negative outcomes of T are equally undesirable. For low values of m, the news received by the policymaker leads them to reduce the probabilities associated with catastrophic declines in temperature, again reducing the need to act.

Appendix E.2. Gamma distributed climate change

To avoid results arising from negative values of T, we can consider the gamma distribution, whose support is the positive real line, as an alternative to the lognormal distribution. In this case, let $f(T) \sim \Gamma(\alpha, \beta)$ and $f^c(T) \sim \Gamma(\alpha_c, \beta_c)$ for shape parameters α, α_c and rate parameters β, β_c. By the properties of the gamma distribution, $\alpha = (m/s)^2$ and $\beta = m/s^2$. In this case, as shown by Hawkins and Wixley (1986), $\sqrt[4]{T}$ will be approximately normally distributed. This approximation works well when $\alpha > 1.5$ (or, equivalently, $m > \sqrt{1.5}s$) but less well otherwise.[12] The mean and standard deviation of this normal distribution are (see, for example, Freeman and Groom (2015)):

$$\mu = \frac{m^{0.25}\Gamma(\alpha+0.25)}{\alpha^{0.25}\Gamma(\alpha)}, \qquad \sigma = \frac{\sqrt{\Gamma(\alpha+0.5)\Gamma(\alpha) - \Gamma^2(\alpha+0.25)}}{\beta^{0.25}\Gamma(\alpha)} \tag{19}$$

with similar expressions for ϕ and Σ when $\alpha_c > 1.5$. We can then, as usual, derive μ' and σ' from equation (9). From this point, the posterior mean and standard deviation of T are given by the fourth and eighth non-central moments of the normal distribution:

$$\begin{aligned} m' &= E\left[\left(\sqrt[4]{T}\right)^4\right] = \mu'^4 + 6\mu'^2\sigma'^2 + 3\sigma'^4 \qquad (20) \\ s' &= \sqrt{E\left[\left(\sqrt[4]{T}\right)^8\right] - m'^2} = \sqrt{\mu'^8 + 28\mu'^6\sigma'^2 + 210\mu'^4\sigma'^4 + 420\mu'^2\sigma'^6 + 105\sigma'^8 - m'^2} \end{aligned}$$

This approach does not lead to simple closed form solutions, but values of m that set $m'^2 + s'^2 = m^2 + s^2$ can be determined using numerical approaches. In Figure A.1, we compare the upper and lower bounds on m with those of the normal distributions for T for both the AR5 and AR6 distributions. We restrict the gamma distribution cases to those where $\alpha > 1.5$, explaining why these lines stop short of the others on the graph.

[12] In more recent work, Kulkarni and Powar (2010) show that a more accurate approximation is $T^{0.246}$ when $a > 1.5$, and $T^{-0.0705-0.178\alpha+0.475\sqrt{\alpha}}$ otherwise. This, though, is not as analytically tractable.

[Insert Figure A.1 around here]

Take the example of the AR5 distribution. Let $M = 3.2°C$, $S = 2°C$ and $m = 2°C$. To ensure that $\alpha > 1.5$, let $s = 1.5°C$. In this case, $\alpha = 1.778$, $\beta = 0.889$, $\alpha_c = 2.56$, $\beta_c = 0.8$. Applying the fourth-root transformation, from equation (19), $\mu = 1.126$, $\sigma = 0.227$ and $\phi = 1.288$, $\Sigma = 0.212$. Equation (9) gives $\mu' = 1.213$ and $\sigma' = 0.155$. Finally, applying equation (20) gives $m' = 2.37°C$ and $s' = 1.20°C$. From this, it is clear that $m' > m$ and $m'^2 + s'^2 > m^2 + s^2$. The expected value of T increases, as does the policymaker's willingness to take action as a consequence of climate change communication. From Figure A.1, this is because $m = 2°C$ lies below the gamma AR5 bound of $2.369°C$. With the same values of m, s, M, S, the the willingness to act would also increase for the lognormal distribution (m again lies below the bound of $2.261°C$) and the normal distribution (m lies between the quadratic roots of $-0.312°C$ and $2.809°C$). However, if $m = 2.51°C$, then the information in AR5 would not cause the policymaker to take more action, while AR6 would because the bound is now $2.87°C$. Again, AR6 has greater policy power than AR5.

In general, as we can see from Figures 2 and A.1, the AR5 bounds fall below/within the AR6 bounds for the lognormal, normal and gamma distributions across the range of s. This analysis shows that results from the gamma distribution are highly similar to those from the lognormal distribution, at least when $\alpha, \alpha_c > 1.5$. The normal distribution gives more distinct results because of the impact of negative values of T, but there still remain clear similarities with the other distributions.

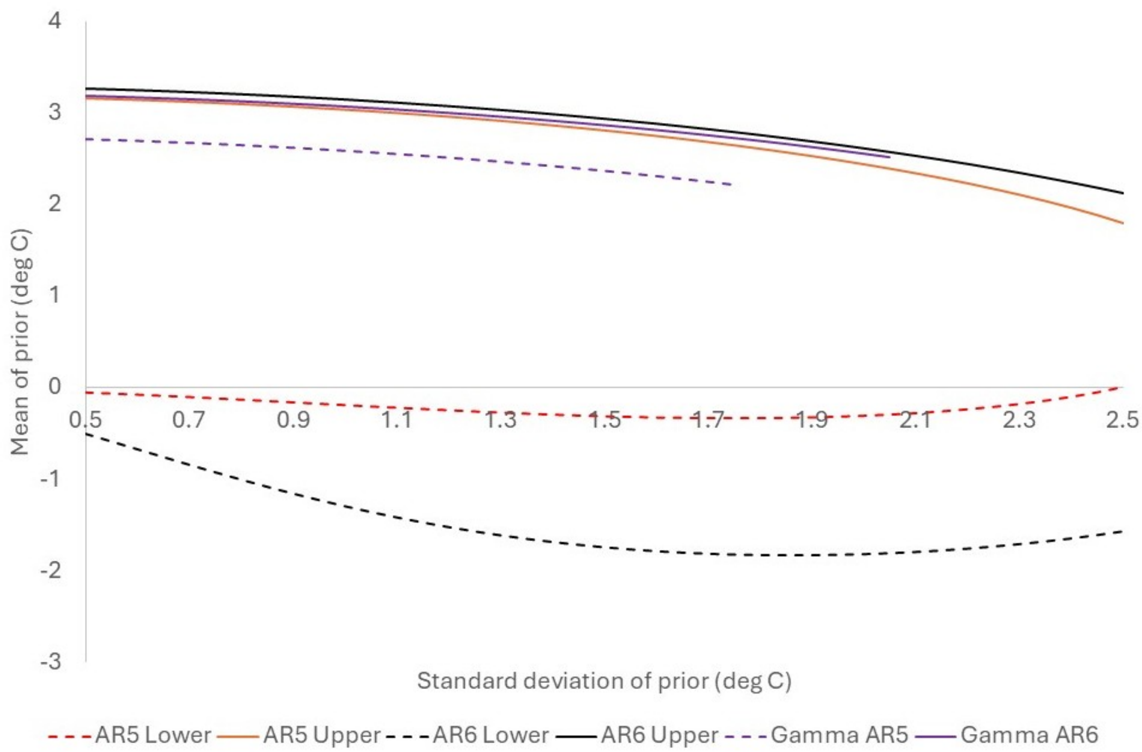


Figure A.1: Upper and lower bounds on the mean of the policymaker's prior, m, for both normally distributed and gamma distributed T. For the policymaker's willingness to take action to increase, m must lie between the upper and lower bounds for the normal distribution, and below the bound for the gamma distribution. This figure presents these bounds for both AR5 and AR6 across a range of values of the standard deviation of the prior, s.

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