# Do Policymakers Respond to Science? Evidence from Climate Policy Stringency

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**ABSTRACT**

We study whether policymakers respond to climate science by examining how projected future temperatures affect climate policy stringency. Using temperature projections from 110 coupled ocean–atmosphere general circulation models, we show that regions facing larger projected temperature increases adopt more stringent climate policies. Our identification strategy exploits within-region changes in temperature projections over time that arise from plausibly exogenous improvements in computing power and advances in climate modeling. The positive effect of projected future temperatures on policy stringency is stronger in regions where projections exhibit lower dispersion across models and where public belief in climate change is higher. At the individual level, policymakers with stronger beliefs in climate change are more likely to incorporate climate projections into their voting behavior, whereas age, gender, and education appear to be less relevant.

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# I. Introduction

To keep the global climate targets within reach, there is a widespread agreement within the scientific community that a substantial reduction in greenhouse gas (GHG) emissions is necessary (Matthews and Wynes, 2022; Meinshausen et al., 2022). For instance, the United Nations Environment Program estimates that GHG emissions need to be reduced by 55 percent in 2035 to align with the 1.5°C pathway (UNEP, 2025). The global adoption of stringent climate policies is essential to reach these GHG emission reduction targets and stave off the worst consequences of climate change (IPCC, 2021; Dekker et al., 2023).[1] However, the factors shaping political decisions on climate policy stringency are so far not well understood.

We investigate a potential determinant of climate policy stringency: the extent to which global climate models project abnormal future temperatures in a country. Abnormal temperatures are a commonly used proxy for the extent of climate change because they are associated with natural disasters and extreme weather events (Rahmstorf and Coumou, 2011; Trenberth et al., 2015). Our main hypothesis, derived from a simple theoretical framework, is that policymakers in regions expected to be more strongly affected by climate change are more likely to adopt more stringent climate policies. The intuition behind this prediction is that the optimal stringency of a climate policy, which has a constant cost but higher payoff in scenarios where climate change is more severe, increases with projected abnormal temperatures.

We rely on abnormal temperature projections from coupled ocean–atmosphere general circulation models. These state-of-the-art climate models, developed within the Coupled Model Intercomparison Project (CMIP), simulate the Earth's climate over the next century and form the backbone of the Intergovernmental Panel on Climate Change (IPCC) Assessment Reports. In total, we use projections from 110 models developed by modeling groups around the world in CMIP Phases 3, 5, and 6. The high spatial resolution of these models allows us to obtain abnormal temperature projections at the country level and, for the United States, at the state level.

[1] For instance, extreme temperatures are associated with lower economic output and increased mortality rates (Somanathan et al., 2021; Carleton et al., 2022). While adaption to changing conditions might reduce some of these effects (Barreca et al., 2016), Waldinger (2022) finds that even gradual climatic changes have negative effects on agricultural productivity and mortality. Furthermore, there is evidence that climate change affects the housing market (Bernstein et al., 2019; Baldauf et al., 2020; Giglio et al., 2021; Bakkensen and Barrage, 2022), municipal bonds (Painter, 2020; Goldsmith-Pinkham et al., 2023), the pricing of bank loans (Correa et al., 2025), and firms in general (Stroebel and Wurgler, 2021; Addoum et al., 2023; Pankratz and Schiller, 2024).

We measure climate policy stringency using the Climate Actions and Policies Measurement Framework (CAPMF). This framework, developed by Nachtigall et al. (2024) at the OECD, provides comprehensive measures of climate policy stringency for 48 countries from 1990 to 2022.[2] Because climate policies in the United States are often decided at the state level, we use a comparable measure of climate policy stringency for U.S. states from 2000 to 2020 from Bergquist and Warshaw (2023).[3] We standardize the policy stringency measures from both databases by subtracting their means and dividing by their standard deviations, and then merge the country-level and U.S. state-level data. The resulting panel covers 99 regions (48 countries and 51 U.S. states, including Washington D.C.) from 2000 to 2020 for U.S. states and to 2022 in the international sample.

We first document a positive correlation between a region's abnormal temperature projections and the stringency of its climate policies. However, this cross-sectional correlation might be biased by omitted region-level factors that simultaneously affect a region's exposure to climate change and its policy stringency. To mitigate this concern, our main specifications rely on the variation of abnormal temperature projections within regions over time. This variation is mainly coming from changes in climate projections across CMIP phases. These changes are largely driven by global improvements in computing power and advances in climate modeling over time, which are plausibly exogenous to local factors that might affect climate policiy stringency.[4] Furthermore, the predictions are modeled under standardized input forcings and hypothetical socioeconomic scenarios, and are not influenced by current policies.

Our results show that a 1°C increase in projected abnormal temperatures increases climate policy stringency by approximately 0.44 standard deviations. This increase in policy stringency mainly comes from international climate policies (e.g., participation in international climate initiatives) and, to a smaller extent, from sectoral climate mitigation policies (e.g., carbon pricing or feed-in tariffs for renewable energy). For cross-sectoral climate mitigation policies, we find no significant impact of projected abnormal temperatures. In addition, we use the Notre Dame Global Adaptation Index from Notre Dame Global Adaptation Initiative to measure climate change adaptation policies and find a similar, yet less significant, positive impact of projected abnormal temperatures on

[2]Other recent studies using this dataset include Stechemesser et al. (2024) and Apeaning et al. (2025).

[3]See Goulder and Stavins (2011) for more details on the interaction between federal and state-level climate policy regulations in the U.S.

[4]The Intergovernmental Panel on Climate Change (IPCC, 2021) states that "models have become increasingly sophisticated as computing power, observations and our understanding of the climate system have advanced (p. 519)." See Lin et al. (2025) for a similar discussion.

countries' readiness for climate change. As the third alternative measure we use emissions, which are a more direct measure for policy stringency compared to CAPMF that does not rely on any manual classifications.[5] In line with the other results, we find that a 1°C increase in projected abnormal temperatures leads to an emission reduction of approximately 25 percent.

The second prediction from our theoretical framework is that projections of abnormal temperatures have a weaker impact on climate policy stringency when they are more uncertain (i.e., when the projections from different climate models and scenarios for the same location are more dispersed). The intuition is that higher uncertainty about future abnormal temperatures increases the risk of more stringent climate policies, which leads risk-averse policymakers to implement less stringent policies for a given level of abnormal temperature projections. To measure the uncertainty of climate projections, we exploit variations across different modeling groups[6] and model specifications for a given location. Our results confirm that the impact of abnormal temperature projections on climate policy stringency decreases with the projections' uncertainty.

The third prediction from our theoretical framework is that the impact of abnormal temperature projections on climate policy stringency depends on the strength of beliefs in climate change among people in a given country or U.S. state. In our theoretical framework, the utility from more stringent climate policies increases with the share of the population that believes in climate change. Intuitively, a policymaker deciding on climate policy stringency benefits more from adopting stringent policies when a larger share of population believes in global warming. We use the Gallup poll on climate change to measure the share of climate believers for the international sample and the Yale Climate Opinion Maps (YCOM) survey for the U.S. sample. Our results show that the impact of abnormal temperature projections is more pronounced in regions with stronger beliefs in climate change.

To further explore how climate projections affect climate policies, we use data on the voting behavior of individual policymakers on climate-related laws for the U.S. from the National Environmental Scorecard. This data base, which was developed by the League of Conservation Voters (LCV), includes voting observations for 1,351 unique policymakers in the House and Senate during our sample period from 2005 to 2022. We match climate projections to policymakers based on their constituency state and measure policymakers'

[5] Nachtigall et al. (2024) and Stechemesser et al. (2024) confirm that higher climate policy stringency leads to lower CO2 emissions.

[6] Examples of modeling groups are the NASA Goddard Institute for Space Studies (U.S.), the Max Planck Institute for Meteorology (Germany), and the Beijing Climate Center (China).

belief in climate change via an LLM text analysis approach based on the corpus of their Wikipedia page or the content of their tweets. When we analyze personal characteristics of policymakers, we find that democratic legislators, those who voted more in favor of climate policies in the past, and those who have a stronger belief in climate change are more likely to adjust their voting behavior to climate projections. Interestingly, we find no impact of a policymaker's age, educational level or background, and gender.

We contribute to several strands of the literature. First, we complement the literature on the determinants of climate policy stringency. Some studies find that exposure to disaster events and extreme weather increases support for climate policies (Ray et al., 2017; Choi et al., 2020; Arias and Blair, 2024), while others find no effect (Nohrstedt et al., 2021; Rowan, 2023; Nohrstedt and Parker, 2024).[7] Other determinants of policy stringency that have been explored are institutional factors such as governmental effectiveness or control of corruption (von Dulong and Hagen, 2024; Lindvall and Karlsson, 2024), factors related to public support of climate policies (Drews and Van den Bergh, 2016; Berkebile-Weinberg et al., 2024; Dechezleprêtre et al., 2025), and global cooperation (Pizer, 2006; Nordhaus, 2015). We add to this literature by showing that scientific information—specifically, abnormal temperature projections from climate models—is an important determinant of climate policy stringency.

We also contribute to the literature on how policymakers and practitioners use scientific climate projections in their decision-making. Weaver et al. (2013) argues that climate models are underutilized as tools to support decision-making, which slows progress in developing informed adaptation and mitigation responses. Similarly, Lemos et al. (2002) notes that potentially useful climate information often goes unused, and Jones et al. (2017) review the literature on the use of long-term climate information in decision-making. Lin et al. (2025) show that uncertainty about future climate projections affects firms' investments in power plants, and Sun et al. (2024) use climate projections to estimate the economic costs of future extreme heat risk. We complement this literature by documenting that climate projections are used by policymakers when determining climate policy stringency, especially if the prediction uncertainty is low and public belief in climate change is high.

Lastly, our analysis of individual policymakers' voting behavior contributes to the broader debate on partisanship and polarization in U.S. politics. For example, Judge et al. (2023) summarize how polarization shapes environmental decision-making, and DellaVigna and Kim (2025) show that party polarization has been a key driver of policy adoption

[7] Nohrstedt et al. (2024), for instance, provide a comprehensive summary of this literature.

over the past two decades. We add to this literature by providing evidence that policy-makers' use and interpretation of scientific information systematically depend on their party affiliation and underlying beliefs. This mechanism offers a potential micro-level explanation for the growing polarization in environmental and climate policy debates.

# II. Theoretical motivation

This section provides a brief theoretical framework to motivate our study and derive our hypotheses. Assume that there exists one country and the decision maker of that country receives information about the projected future temperature from scientific climate modeling. The projections of the future abnormal temperature $t$ follows the distribution

$$t \sim \mathcal{N}(\mu, \tau^{-1}), \tag{1}$$

where $\tau$ equals $\frac{1}{\sigma^2}$, with $\tau$ representing the projection precision and $\sigma$ the uncertainty about temperature projections. The decision maker needs to decide the stringency of the country's climate policy, which is denoted as $x$, today. The cost of enacting the climate policy equal its stringency $x$, i.e., more stringent climate policies come at higher (economic) cost. In the future, the abnormal temperature $t$ is revealed, and the payoff from the climate policy is $xt$. Thus, the expected payoff of the climate policy today is given by $E[xt]$ and the expected return by $E[xt - x]$.

Consider a mean-variance utility of the return from the climate policy, which is $E[xt - x] - \frac{1}{2}\gamma^2 Var[xt]$, where $\gamma$ captures the risk aversion level. Further assume that $p$ percent of the population believe in the climate change and $1 - p$ percent of the population do not. For the believers, they trust the climate models and therefore believe that the future abnormal temperature $t \sim \mathcal{N}(\mu, \tau^{-1})$. The non-believers think that the future temperature change will be zero on average, but they also face uncertainty about the distribution of the future abnormal temperature. Thus, their perception of the future abnormal temperature is $t \sim \mathcal{N}(0, \tau^{-1})$.

We can write down the utility of believers as $\mu x - x - \frac{1}{2\tau}\gamma^2 x^2$ and as $0x - x - \frac{1}{2\tau}\gamma^2 x^2 = -x - \frac{1}{2\tau}\gamma^2 x^2$ for non-believers. The overall utility in the country is the weighted average of the utilities of believers and non-believers, which equals

$$U = p\mu x - x - \frac{1}{2\tau}\gamma^2 x^2 \tag{2}$$

The first and second-order condition of this maximization problem are

$$p\mu - 1 - \frac{\gamma^2}{\tau}x = 0 \text{ and } -\frac{\gamma^2}{\tau} < 0 \text{ , respectively.}$$

The climate policy stringency $x^*$ that maximizes the weighted utility function in the country is therefore given by

$$x^* = \frac{p\mu - 1}{\gamma^2}\tau \tag{3}$$

We can derive several empirical predictions from this optimality condition.[8] For the mean of projected abnormal temperatures $\mu$ we find that

$$\frac{\partial x^*}{\partial \mu} = \frac{p\tau}{\gamma^2} > 0 \tag{4}$$

This result directly leads to our first hypothesis regarding the impact of average abnormal temperature projections on climate policy stringency:

**Hypothesis 1** (H1)**.** *Higher abnormal temperature projections lead to more stringent climate policies.*

Equation 4 also shows that the positive relationship between temperature projections and policy stringency increases with the information precision $\tau$ and deceases with the uncertainty about temperature projections $\sigma$. Thus, our second hypothesis that we test in the empirical part is:

**Hypothesis 2** (H2)**.** *The impact of temperature projections on climate policy stringency decreases with uncertainty about future temperature projections.*

The third insight from Equation 4 is that the share of the population who believes in climate change $p$ increases the sensitivity of policy stringency to abnormal temperature projections. Consequently, our third and last hypothesis is:

**Hypothesis 3** (H3)**.** *The impact of temperature projections on climate policy stringency increases with the share of the population who believes in climate change.*

We also find that the level of risk aversion $\gamma$ reduces the impact of abnormal tem-

[8] In our empirical setting, we use the average abnormal temperature projection as $\mu$ and the standard deviation of the abnormal temperature projections across different models and scenarios as $\sigma$.

perature projections on policy stringency. However, since we cannot measure the level of risk aversion empirically, we do not derive any hypothesis for testing in this part.

# III. Data

This section introduces the data that we use in the empirical analysis and describes the methods used to construct the key variables. Summary statistics for key variables are reported in Table 1, and Appendix A provides a description of the variables.

## *A. Climate Policy Stringency*

Stringent climate policies are crucial for reaching global GHG emission reduction targets (Fowlie et al., 2012; Colmer et al., 2025; Bai and Ru, 2024). Dekker et al. (2023), for instance, finds the climate target stringency explains most of the spread in greenhouse gas emissions. To measure the stringency of climate policies in the international sample, we rely on the OECD Climate Actions and Policies Measurement Framework (CAPMF), which was developed by Nachtigall et al. (2024). This database offers a relatively broad geographical coverage of 51 countries including E.U. (the data for the United States and Brazil are currently missing), a long time series coverage from 1990 to 2022, and detailed measurements of climate policy stringency. The CAPMF is considered as the successor of the former OECD Environmental Policy Stringency (EPS) index by Botta and Koźluk (2014).[9]

In the CAPMF, policy stringency is calculated in a bottom-up manner by categorizing climate policies into three blocks (level 1), 15 modules (level 2), 56 policies (level 3), and 130 characteristics (level 4). The details of this hierarchy structure and the categories are shown in Figure 1. A value from 0 to 10 is assigned for each of the 130 policies in every country and year based on the quantile of the stringency the country is in among all countries and all years, with 0 meaning that the policy is not implemented, and 10 meaning that the strictest policy is enacted. Then, following to the hierarchy structure, the value of upper layer is the average of the values of the lower layers. Our data is

[9] Alternative sources for information on climate policies include the Climate Watch Data by World Resources Institute, Climate Policy Data Base by NewClimate Institute, PAMS Database by IEA, Greenhouse Gas Policies and Measures in Europe by European Environment Agency, Climate Change Performance Index by GermanWatch, and the Policy Instruments for the Environment (PINE) Database by OECD. However, compared to the CAPMF, these sources either have a less comprehensive geographical or time series coverage or a less detailed measurement of climate policy stringency. Steinebach et al. (2024) provides a more comprehensive overview on these databases.

downloaded from the OECD data explorer, and is lastly updated in June 2024. Our main measure for policy stringency is the average of the values of all 15 modules (level 2) variables for each country-year observation.[10]

In the United States, many climate-policy related regulations are decided on the state level (Goulder and Stavins, 2011). Therefore, we supplement the international sample with the state-level climate policy stringency data for the U.S. We rely on the data from Bergquist and Warshaw (2023) who develop state-level climate policy stringency measures for all 50 U.S. states and Washington, DC from 2000 to 2020. Similarly to the CAPMF, they collect information on 25 individual policies and develop an aggregate index of state climate policy stringency. Although this is, to the best of our knowledge, the most similar data on the state-level to the CAPMF database, it is worth to note that the specific category classifications, the aggregation methods, and the numeric scales are different. Thus, before combining the international and the U.S. data, we normalize the policy stringency values by subtracting their means and dividing by their standard deviations.[11] Our main policy stringency variable $\text{Stringency}_{r,t}$ is the normalized climate policy stringency for region $r$ in year $t$. This measure covers 48 countries from 2005 to 2022 and 51 U.S. states from 2005 to 2020.[12] For illustration, we plot this variable for the years 2005, 2010, 2015, and 2020 in Figure 2.

Because our main measures focus mostly on climate mitigation policies, we also investigate climate adaption policies in a separate test.[13] The Notre Dame Global Adaptation Index (ND-GAIN) from Notre Dame Global Adaptation Initiative brings together more than 40 core indicators to measure vulnerability and readiness of 182 U.N. countries from 1995 to 2025. It is widely used by firms, governments, and academics in various fields (Dechezleprêtre et al., 2025). We rely on the $\text{Readiness}_{r,t}$ indicator from the ND-GAIN Country Index as our measure for how comprehensive a country's adaptation policies are. This measure captures a country's ability to leverage investments and convert them to adaptation actions by considering the three components economic readiness, governance readiness, and social readiness.

Lastly, we collect data on emissions. We obtain state-level CO2 emissions for the

[10] An alternative approach, for which we find very similar results, is to use the average of the level 1 blocks (see robustness tests).

[11] Furthermore, we will show our main results separately for both samples, which show robustness and consistence on both country and state levels, regardless the difference in data sources.

[12] We exclude Russia from our sample due to its large area that spans multiple climate zones.

[13] Climate change adaptation policies are highly context-specific and often qualitative. For example, flood walls in the Netherlands can be regarded as a way to adapt sea-level rising, while in Kenya, drought-resistant crops may be viewed as a way to adapt global warming.

United States from the Energy Information Administration (EIA). For the international sample, we obtain emission data from the World Bank, which comes from a collaboration between the European Commission, Joint Research Centre (JRC), the International Energy Agency (IEA). For the international data, we obtain both CO2 and GHG emissions, while we only obtain CO2 data for the U.S. sample. Our main emissions measure is $CO2_{r,t}$, which is defined as the emission in region $r$ and year $t$ excluding land use, land-use change and forestry in megatons.

## *B. Climate Predictions*

Coupled atmosphere–ocean general circulation models are used to project Earth's climate over the next century. To standardize global climate modeling, the Coupled Model Intercomparison Project (CMIP) was founded in 1995. This project defines experiment protocols, formats, standards, and distribution mechanisms and forms the scientific backbone of the Climate Assessment reports by the U.N. Intergovernmental Panel on Climate Change (IPCC). The first widely available CMIP project was Phase 3, which formed the scientific basis for the IPCC Assessment Report 4 in 2007. Phase 5 was used for the IPCC Assessment Report 5 in 2014. The most recent version is Phase 6; the related IPCC Assessment Report 6 was published in 2021. We assume that the models of the phases became publicly available after the CMIP workshop for a specific phase was held. The corresponding dates are March 2005 for Phase 3, March 2012 for Phase 5, and March 2019 for Phase 6.

The CMIP provides inputs (also called "climate forcings") that enable the climate modeling groups to run their models. These factors include, among others, scientific observations on emissions and the concentration of greenhouse gases, sea-surface temperatures, population density, and land usage. The CMIP also defines different potential future scenarios for climate modeling. There are three scenarios (A1B, A2, B1) in CMIP Phase 3 and four scenarios in Phase 5 (RCP26, RCP45, RCP60, RCP85) and Phase 6 (SSP126, SSP245, SSP370, SSP585). In our analysis, we consider the A2, RCP85, and SSP585 scenarios as pessimistic scenarios, the A1B, RCP45, RCP60, SSP245, SSP370 scenarios as average scenarios, and the B1, RCP26, SSP126 scenarios as optimistic scenarios. Inputs and scenarios are standardized and used by all climate modeling groups to project the climate for the next century.

In each phase, various modeling groups around the globe develop climate models, which we obtain from the Earth System Grid Federation server (CMIP6 link; CMIP5

link; CMIP3 link) and the archive of the German Climate Computing Center (link). For a model to be included, we require the availability of near-surface air temperature (TAS) projections and historical simulation data. In CMIP Phase 3, we are able to obtain the projections of 22 models and 59 model-scenario pairs from 16 modeling groups in 12 countries. In Phase 5, we use projections from 42 models and 125 model-scenario pairs from 29 modeling groups in 14 countries. In Phase 6, we use 46 models consisting and 151 model-scenario pairs from 42 modeling groups in 15 countries. Overall, we obtain 110 models and 335 model-scenario pairs. Details about the modeling groups and their models are available in Appendix B and Appendix C, respectively.

For each model, we obtain the raw data of near-surface air temperature (TAS) projections with monthly frequency as shape files. We spatially match the model projections, which are provided as grid files, to countries and U.S. states in R. The abnormal temperature projections are obtained by subtracting the average temperatures between 1900 and 1999 in a month and region from the projected temperature for the same month and region. The historical temperature comes from the historical simulation of the specific model.[14] For illustration, we plot the future temperature projections for 2040 by different CMIP Phase 5 models in Figure 3, and the average abnormal temperature projection for 2050 by different CMIP Phases in Figure 4.

Based on the assumption that the CMIP model projections are available to policymakers and the public after the main workshop for a CMIP phase was held, we rely on Phase 3 projections for the period from 2005 to 2011, Phase 5 projections from 2012 to 2018, and Phase 6 projections from 2019 to 2022. In our baseline specification, we use a projection horizon of 25 years and a buffer period of one year between the sample year and the start of the projection period. Consequently, our main variable Abn $\text{Temp}_{r,t}^{t+1/t+26}$ for region $r$ and year $t$ is calculated by averaging the monthly abnormal temperature projections from $t+1$ to $t+26$ across all models and scenarios in the corresponding CMIP phase. To measure the uncertainty of the projection, we construct the variable Abn Temp $\text{SD}_{r,t}^{t+1/t+26}$ for region $r$ and year $t$ as the average monthly standard deviation of abnormal temperature projections from $t+1$ to $t+26$ across models and scenarios of the corresponding CMIP phase. Appendix D provides an illustration of this time structure.

[14] In this sense, the abnormal temperature is the predicted future temperature calibrated with the model-specific historical baseline. This is common practice since different models are likely to have different absolute values for different variables; see IPCC (2021) pp. 189 and 190 for a detailed explanation.

## C. *Climate Change Belief*

To measure public beliefs about climate change, we use data from Gallup's World Poll conducted in 2019 and 2021. This survey covers 145 countries, including all countries in our sample.[15] For U.S. states, we use the Yale Climate Opinion Maps (YCOM) from Howe et al. (2015), which provide subnational measures of climate change beliefs. We rely on two conceptually similar questions from these sources: Gallup's "Climate change will be a very serious threat/somewhat serious threat/not a threat/don't know to the country in the next 20 years" and YCOM's "Do you believe global warming will start to harm people in the United States now/within 10 years?" Because Gallup data are available only for two years and YCOM begins in 2010, we use average beliefs by region rather than time-series variation, assuming that cross-sectional differences in climate change beliefs are relatively stable over time (Marlon et al., 2022). Accordingly, we construct the variable $\text{Belief}_r$ as the average share of respondents in region $r$ who provide a positive (i.e., harm-acknowledging) answer.

## D. *Policymaker's voting*

To better understand how climate science translates into policy stringency, we investigate the voting behavior of the policymakers responsible for enacting such regulations. This test is restricted to the United States, for which we are able to utilize the National Environmental Scorecard from the League of Conservation Voters (LCV). This database evaluates how climate friendly the voting behavior of members of the U.S. congress. The LCV provides scores for each policymaker based on their voting record on important and environmentally related votes selected by a consensus of experts from major environmental organizations. Our sample comprises 10,699 yearly LCV score observations from 1,351 unique policymakers in the House and Senate from 2005 to 2022. The variable $LCV\ Score_{i,t}$ is then defined as the LCV score of policymaker $i$ in year $t$. Following the literature, we employ this score as a proxy for a legislator's support of climate-aligned policies (Fisher and Taylor, 2006; Brulle et al., 2012).[16]

Furthermore, to measure policymakers' age, gender, party affiliation, and chamber, we use data from GovTrack.us, which publishes statistics on members of the U.S.

[15] The UN's Peoples' Climate Vote 2024 is an alternative source, but it covers only 24 of our sample countries. The World Values Survey has broader country coverage, but questions on climate change attitudes are only included in the forthcoming Wave 8.

[16] Note that while our main analysis measures policy stringency at the state level, the voting data reflects policymakers behavior at the federal level.

House of Representatives and the Senate. From this source, we construct the variables $\text{Age}_{i,t}$, $\text{Female}_i$, $\text{Democrat}_i$, and $\text{Senate}_{i,t}$, covering all policymakers in our sample. To measure educational background and belief in climate change, we implement an LLM-based text analysis approach using corpora drawn from each policymaker's Wikipedia page and Twitter posts. Based on these texts, we construct $\text{Belief Wiki}_i$, $\text{Belief Tweet}_i$, $\text{Belief Tweet Wiki}_i$, and $\text{Edu Score}_i$ for those policymakers with sufficient available data. The detailed methodology is described in Appendix E. In addition, we implement a conventional text analysis approach by examining whether a policymaker has tweeted about topics related to the IPCC (including key words such as 'IPCC', 'Intergovernmental Panel on Climate Change', 'IPCC Assessment Report', etc.), and construct a binary indicator $\text{Tweet IPCC}_i$ for all policymakers for whom we collected tweets.

### *E. Other Variables*

In addition to the main variables described above, we also use country-level and state-level controls from offical sources. To construct GDP per capita, we collect country-level GDP and population data from the World Bank's World Development Indicators (WDI) database, and state-level GDP data (in constant 2017 USD) from the U.S. Bureau of Economic Analysis (BEA), together with state-level population data from the U.S. Census. In addition, we construct a variable to capture historical temperature changes using data from NOAA's Global Historical Climatology Network. The variable $\text{Abn Temp}_{r,t}^{t-2/t}$ denotes the average abnormal temperature for region $r$ over the period from $t-2$ to $t$, relative to the baseline period 1900–1999, computed using all available stations.

## IV. Results

### *A. Abnormal temperature projections and policy stringency*

We first provide graphical evidence on the relationship between climate projections and climate policy stringency in Figure 5. In subplot (a) of this figure, the x-axis is the abnormal projected temperature in a country and CMIP phase and the y-axis is the average standardized climate policy stringency in the same country and CMIP phase. Both the international observations (in blue) and the U.S. observations (in red) are scatter closely to the fitted line. While there are a few outliers that are slightly diverted, we find no observations in the left-top or right-bottom. However, this positive relationship

should be interpreted with caution because it might be driven by omitted factors on the country level. In subplot (b), we replace the y-axis with the average yearly change of the standardized climate policy stringency within a country and the x-axis with the average yearly percentage change of projected temperatures. In line with the previous subfigure, we again find a positive correlation.

In a second step, we implement an fixed-effects regression that helps to further mitigate concerns about unobserved factors. In particular, we include a year-fixed effect that absorbs common time trends across all regions and a region-fixed effect that absorbs all factors on the region level that do not change over time. As is discussed before, the variation that we exploit in this specification comes from changes in abnormal temperature projections over time, which are mostly driven by differences in climate modeling across the CMIP phases. Our empirical specification is as follows:

$$\begin{aligned} \text{Stringency}_{r,t+1} =& \alpha + \beta_1 \text{Abn Temp}_{r,t}^{t+1/t+26} \\ &+ \vec{\beta_2}\vec{X}_{r,t} + \alpha_r + \alpha_t + \epsilon_{r,t+1} \end{aligned} \tag{5}$$

The effect of abnormal temperature projections on climate policy stringency is estimated by coefficient $\beta_1$. A vector of control variables is denoted as $\vec{X}_{r,t}$, time fixed effects as $\alpha_t$, and region fixed effects as $\alpha_r$. The dependent variable is measured in $t+1$, assuming that it takes time to enact laws after the abnormal temperature projection changed in year $t$. T-statistics based on robust standard errors clustered by regions are reported.

The results are shown in the Panel A of Table 2. Columns 1 and 2 provide simple cross-sectional estimates without fixed effects. In these models, we find that a 1°C increase in the abnormal temperature projection is associated with an approximately one standard deviation increase in climate policy stringency. When we add region and year fixed effects in Columns 3 and 4, the coefficient estimate for $\beta_1$ remains positive and statistically significant, but its magnitude decreases. Now, a 1°C increase in the abnormal temperature projection leads to an increase of 0.44 to 0.48 standard deviation in climate policy stringency. These results, which show that climate projections indeed affect climate policy stringency, provide support for Hypothesis 1.

Since the policy stringency measure for the international and U.S. sample are from different sources and there are substantial differences in their methodologies, we re-estimate the previous regression for both samples separately in the Panel B. We find that the coefficient estimate for $\beta_1$ is statistically significant in both samples and slightly larger for the U.S. sample (0.41 vs. 0.61). These results show that the positive impact of abnormal

temperature projections on climate policy stringency exists in both samples, which alleviates potential concerns that our results are driven by the combination of both samples. Furthermore, this finding indicates that the pattern we have documented is general and not restricted to any particular region.

Next, we explore how the result changes for alternative specifications. The baseline model for the variations that we explore here is Column (3) of Table 2. Graphical results are shown in Figure 6 and coefficient estimates for Abn Temp in Table 3. We first separate the projections by the hypothetical scenarios to infer which scenarios decision makers pay most attention to. Subplot (a) shows the regression coefficient and the corresponding confidence intervals for optimistic, average, and pessimistic scenarios. We find that the average scenario has the strongest impact on policy stringency, which indicates that policy makers pay most attention to that. In subplot (b), we use percentiles of the abnormal temperature projections across all models and scenarios instead of the average that we use in our baseline specification. We find the strongest effect for the 50th to 70th percentile, again indicating that policy makers pay more attention to "average" temperature projections compared to the tails of the distribution. We also vary our time structure to check the robustness. Subplot (c) and (d) present the coefficient estimates when using different lengths of the projection horizon (from 10 to 50 years) and different time lags between the sample year and the start of the projection period (from one to five years). Neither of these alternative specifications has a substantial impact on the results.

Table 3 also provides several additional robustness tests. We use the logarithm of Abn Temp, climate policy stringency in year $t$ or $t+2$ instead of $t+1$, cluster standard errors by region and year (instead of region only), and calculate climate policy stringency as the average of the three level 1 blocks of CAPMF instead of the average of the 15 level 2 modules. None of these variations has a substantial impact on the coefficient estimate for Abn Temp, which provides evidence for the stability of the effect that we have documented in this section.

## *B. Disaggregating climate policies by type*

As the CAPMF provides a detailed taxonomy of the climate policies, we can identify which specific type of climate policies are affected by climate projections for the international sample. For this purpose, we split the climate policy stringency into the three level 1 blocks, i.e., sectoral policies, cross-sectoral polices, and international policies. Sectoral policies include, for instance, carbon pricing for electricity generation; an example for

cross-sectoral policies are general emission targets; international policies include, for example, the participation in international climate initiates (see Figure 1 for more details).

The results are shown in Panel A of Table 4. The estimated effect is positive for all three policy types, but statistically significant only for sectoral and international policies. In terms of economic magnitude, we find the strongest effect of temperature projections on international policies, followed by sectoral and cross-sectoral policies. Given the global nature of climate change and the need for international cooperation to limit global warming, these results support the view that regions more affected by climate change are more active in such international cooperation. Since sectoral and cross-sectoral policies are likely to have limited effects on the extent of climate change for smaller countries with lower emission levels, international policies also provide these regions with an opportunity to exert influence.

The CAPMF mainly focuses on the stringency of climate mitigation policies, largely ignoring climate adaption policies. Thus, we supplement our main analysis with the readiness score from the ND-GAIN index to measure climate change adaptation policies. The results are shown in the Panel B of Table 4. We find that countries' overall readiness for climate change increases with abnormal temperature projections. This effect is mostly driven by their economic readiness, which measures the ability of countries to accept investments for climate adaptation by assessing its business environment. For social readiness, which captures factors such as social inequality and education that enhance the mobility of investment and promote adaptation actions, we find a negative estimate for $\beta_1$. However, given the limited time-series variation of such social factors, this result should be interpreted with caution.

In addition to the policy-related measures, we also explore the impact of abnormal temperature projections on greenhouse gas emissions as an alternative outcome measure. Recent studies, including Nachtigall et al. (2024), Bergquist and Warshaw (2023), and Stechemesser et al. (2024), have identified a negative correlation between climate policy stringency and emission, suggesting that emissions can serve as reliable indicators of climate policy stringency. In contrast to the policy-related measures, emissions data do not require any manual classifications. The results are shown in the Panel C of Table 4. The specifications in Columns 1 and 2 use the logarithm of CO2 emissions for both the international and U.S. sample as dependent variable. We find that higher projected abnormal temperatures reduce CO2 emissions, with a 1°C increase in the abnormal temperature projection leading to an emission decrease by approximately one quarter. Results for total GHG emissions, which are only available for the international sample, are shown in

Columns 3 and 4.

## C. *The role of projection uncertainty and climate belief*

Hypothesis 2 and 3 predict that the positive relationship between abnormal temperature projections and climate policy stringency relationship decreases with projection uncertainty and increases with the share of the population who believe in climate change. To test the role of projection uncertainty, we adjust our baseline regression framework from the previous subsection as follows:

$$\begin{aligned}\text{Stringency}_{r,t+1} =& \alpha + \beta_1 \text{Abn Temp}_{r,t}^{t+1/t+26} \\ &+ \beta_2 \text{Abn Temp SD}_{r,t}^{t+1/t+26} \\ &+ \beta_3 \text{Abn Temp} \times \text{Abn Temp SD}_{r,t}^{t+1/t+26} \\ &+ \vec{\beta_4} \vec{X}_{r,t} + \alpha_r + \alpha_t + \epsilon_{r,t+1},\end{aligned} \tag{6}$$

where all interacted variables are centered. The results are reported in Table 5. We start with a simple model without any control variables in Column (1), add controls for Log(GDP) and past abnormal temperatures in Column (2) and Column (3), and interact those control variables with average abnormal temperature projections in Columns (4). The coefficient for the average abnormal temperature projection remains positive and statistically significant across all models, while the impact of projection uncertainty is small and statistically insignificant. The coefficient estimate for $\beta_3$, which captures the interaction effect between average abnormal temperature projections and the uncertainty of projections across models and scenarios, is negative and statistically significant. In terms of magnitude, 1 °C increase in the projection standard deviation reduces the marginal effect of projected abnormal temperatures on policy stringency by 0.55 units. This result implies that the impact of abnormal temperature projections on climate policy stringency declines as the projection uncertainty increases. Conversely, where projections are more precise (i.e., uncertainty is lower), a higher abnormal temperature projection has a stronger impact on policy stringency.

To test for the role of climate belief, we adjust our baseline framework as follows:

$$\begin{aligned}\text{Stringency}_{r,t+1} =& \alpha + \beta_1 \text{Abn Temp}_{r,t}^{t+1/t+26} \\ &+ \beta_2 \text{Abn Temp} \times \text{Belief}_r \\ &+ \vec{\beta_3} \vec{X}_{r,t} + \alpha_r + \alpha_t + \epsilon_{r,t+1},\end{aligned} \tag{7}$$

where all interacted variables are centered. The results are reported in Table 6. We start with a simple model without any control variables in Column (1), add controls for Log(GDP) and past abnormal temperatures in Column (2) and Column (3), and interact those control variables with average abnormal temperature projections in Columns (3) and (4). The base effect of future abnormal temperature projections is positive and significant, while the coefficient estimate for people's climate change belief is absorbed by the region fixed effects. The coefficient estimate for $\beta_3$, which captures the interaction effect between abnormal temperature projections and people's climate belief, is positive and statistically significant. In terms of magnitude, a region where 10 percent more people believe in climate change will have a stronger marginal effect of projected abnormal temperatures on policy stringency by 0.131 units. This result implies that the impact of abnormal temperature projections on climate policy stringency is attenuated in regions where belief in climate change is low, but becomes stronger in regions with higher levels of belief. In other words, policymakers respond more to abnormal temperature projections when the local belief in climate change is stronger.

## *D. Policymakers' characteristics and their voting behavior*

In the previous section, we examined how projections of future abnormal temperatures influence the stringency of climate policies. To better understand the micro-foundations of how these policies are enacted, we now turn to individual policymakers' voting behavior on climate- and environment-related legislation. In contrast to the previous analysis, our main focus here is on how specific characteristics of policymakers shape their responses to climate projections.

The dependent variable in the policymaker-level analysis is the LCV score, which measures how environmentally friendly a policymaker's voting behavior is in a given year. We estimate a high-dimensional fixed-effects model with region-by-year fixed effects and policymaker fixed effects, which absorb time-varying regional factors, time effects, and time-invariant characteristics of policymakers. The model is specified as follows:

$$\begin{aligned} \text{LCV Score}_{i,t+1} =& \alpha + \beta_1 \text{Abn Temp}_{r,t}^{t+1/t+26} \times \text{Characteristic}_i \\ &+ \alpha_{r,t} + \alpha_i + \epsilon_{i,t+1}, \end{aligned} \tag{8}$$

where $i$ indicates policymakers, $t$ years, and $r$ regions.

In Panel A of Table 7, we examine policymakers' age and gender, education score (High School or below, Bachelor, Master, PhD or equivalent), and a dummy that indicates

whether they did attend an Ivy League university. We find that neither of these factors has an impact on how abnormal temperature projections affect the voting behavior of a policymaker. In Panel B, we first explore policymakers' historical voting scores in favor of climate-friendly policies. We find that higher abnormal temperature projections translate into more climate-friendly voting behavior for policymakers who voted more in favor of climate-friendly policies in the past. This finding holds true for the continuous historical LCV score in Column (1) and a dummy that equals one if a policymaker has a historical of LCV score of above 50 percent in Column (2). Column (3) shows that this responsiveness is also significantly stronger among Democrats, consistent with the conventional view that Democrats are, on average, more supportive of environmental protection. We find no significant difference between policymakers in the house and senate in Column (4).

In Panel C, we focus on the climate beliefs of policymakers. We apply four different policymaker-level belief measures. The first is Tweet IPCC$i$, which indicates whether a policymaker has tweeted about topics related to the IPCC reports. The other three measures, which are all based an LLM-based text analysis approach, are Belief Tweet$i$, Belief Wiki$i$, and Belief Tweet Wiki$i$. These variables indicate whether a policymaker strongly denies (score of minus two) or strongly accepts (score of plus two) climate change. See Appendix A and Appendix E for more details on the construction of these variables. Across all four measures, the interaction between future abnormal temperature projections and policymakers' climate belief is positive and statistically significant. This finding shows that the effect of abnormal temperature projections on subsequent pro-environment voting is stronger for policymakers who have a higher belief in climate change. The consistency of signs, magnitude, and significance levels across alternative belief proxies also suggests that the moderating role of climate belief is strong and not driven by a particular measurement choice.

# V. Conclusion

We provide empirical evidence that scientific information about climate projections is an important determinant of climate policy stringency. Our identification strategy relies on the variation of temperature projections over time, which is mainly driven by improvements in computing power and advances in climate modeling and plausibly exogenous to local factors. The effect is primarily driven by international policies and, to a lesser extent, by sectoral policies. However, the impact of climate projections on policy strin-

gency is not uniform. First, when future climate projections are more uncertain (i.e., when the projections from different climate models and scenarios for the same location are more dispersed), the estimated effect of projections on policy stringency is weaker. Second, belief in climate change amplifies the relationship between climate projections and policy stringency.

At the level of individual policymakers, we find that their belief in climate change, as measured by an LLM-based textual analysis, is crucial for their response to abnormal temperature projections. Only policymakers who believe in climate change vote more in favor of environmentally friendly policies when projected abnormal temperatures increase. Interestingly, we find no evidence that policymakers' age, gender, or education affects the impact of abnormal temperature projections on their voting behavior. This evidence suggests that only some policymakers respond to scientific information about climate change, providing a potential micro-level explanation for the growing polarization in environmental and climate policy debates.

By documenting a systematic link between forward-looking climate projections and climate policy choices, our results show that scientific information is incorporated into the policy-making process. This finding indicates that climate modeling is highly relevant for climate policy in practice. However, the impact of climate modeling on policy making crucially depends on its precision and on how strongly voters and policymakers believe in climate change. Thus, improving the precision of climate models and shifting voters' and policymakers' beliefs about climate change can increase the likelihood that scientific predictions translate into timely and stringent climate policy.

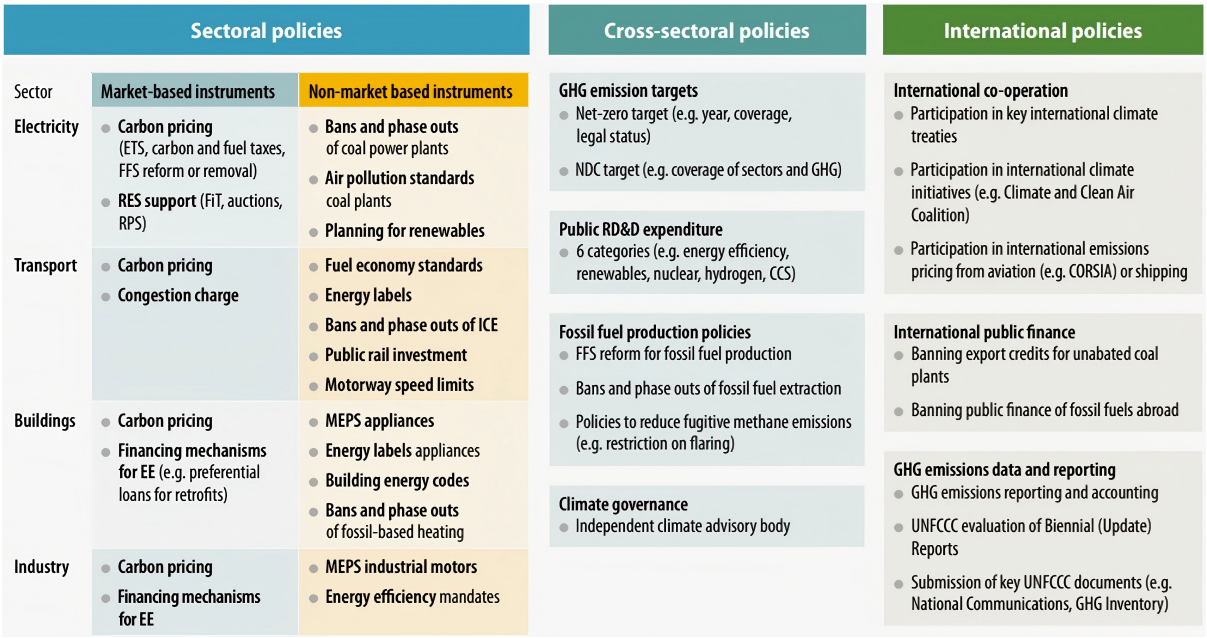



Figure 1: This figure illustrates the structure of the Climate Actions and Policies Measurement Framework (CAPMF) from Nachtigall et al. (2024).

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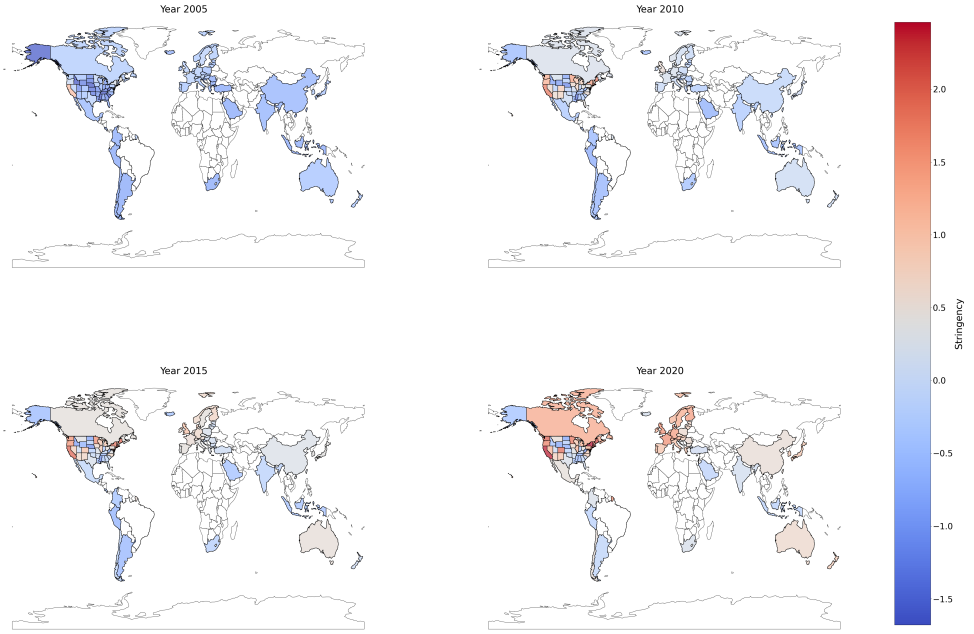
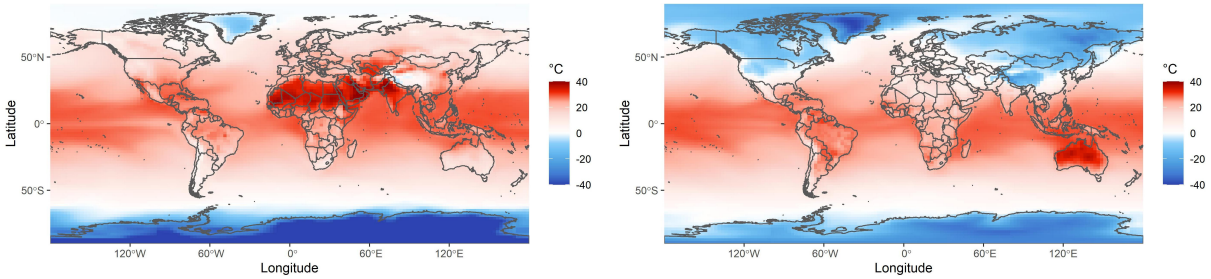


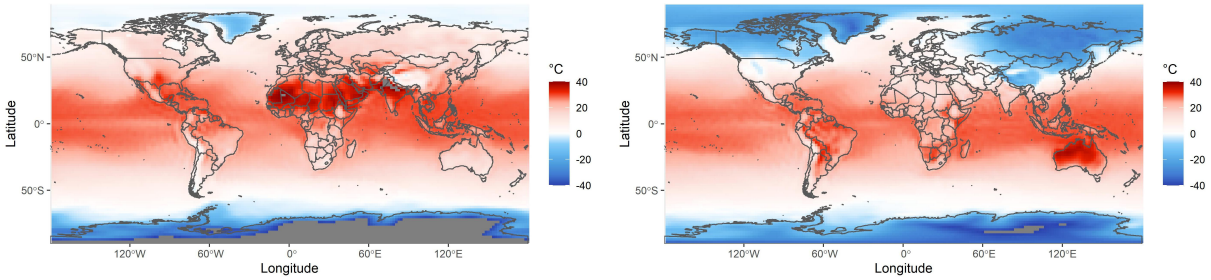

Figure 2: This figure shows the country/state-level policy stringency for the years 2005, 2010, 2015, and 2020. The policy stringency is standardized using the mean and standard deviation of countries and U.S. states, respectively.




(a) GFDL-CM3 model, June 2040



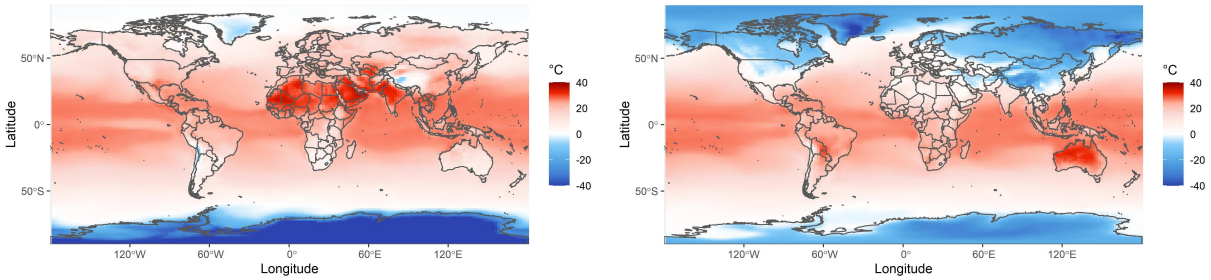

(b) GFDL-CM3 model, December 2040




(c) MPI-ESM model, June 2040




(d) MPI-ESM model, December 2040




(e) INM-CM4 model, June 2040




(f) INM-CM4 model, December 2040

Figure 3: This figure shows near-surface air temperature projections (in °C) of several exemplary CMIP5 models for June and December 2040 using the RCP 4.5 scenario. Temperatures are winsorized at plus/minus 40 °C for this illustration. See Appendix C for climate data sources.

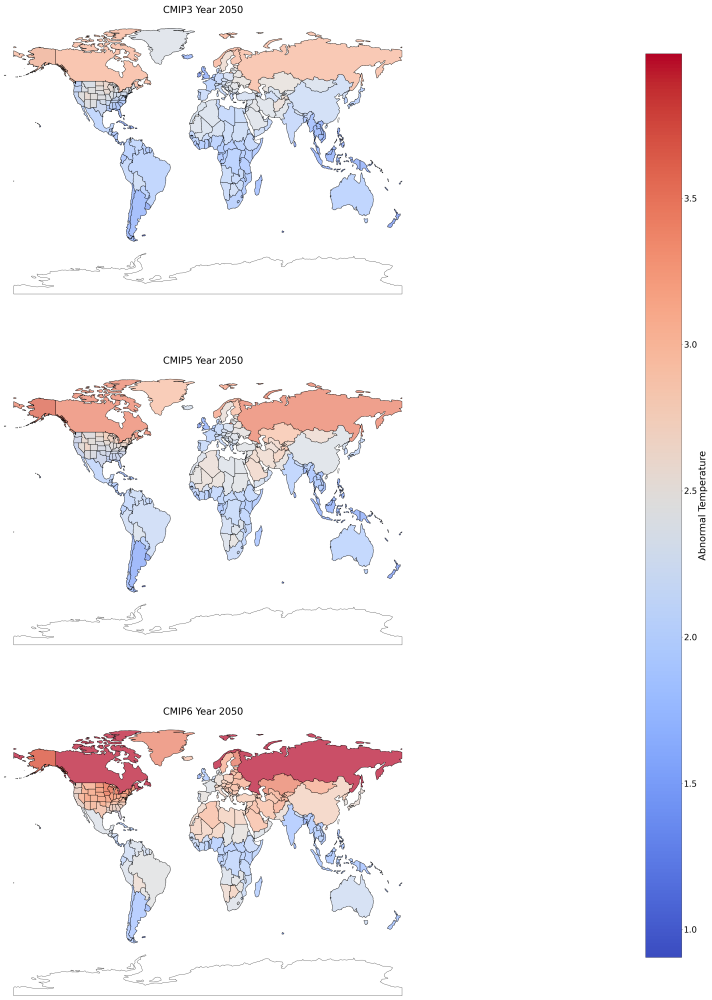
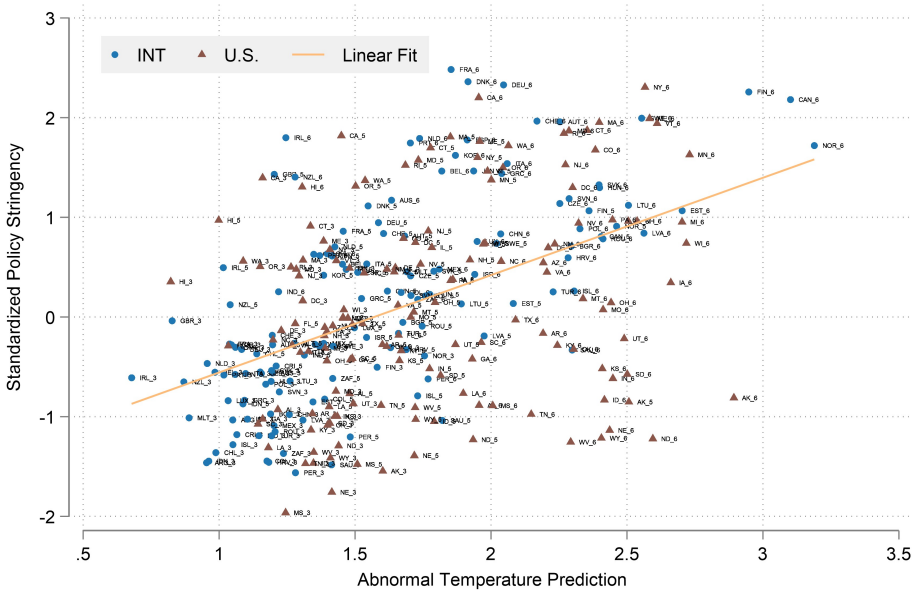
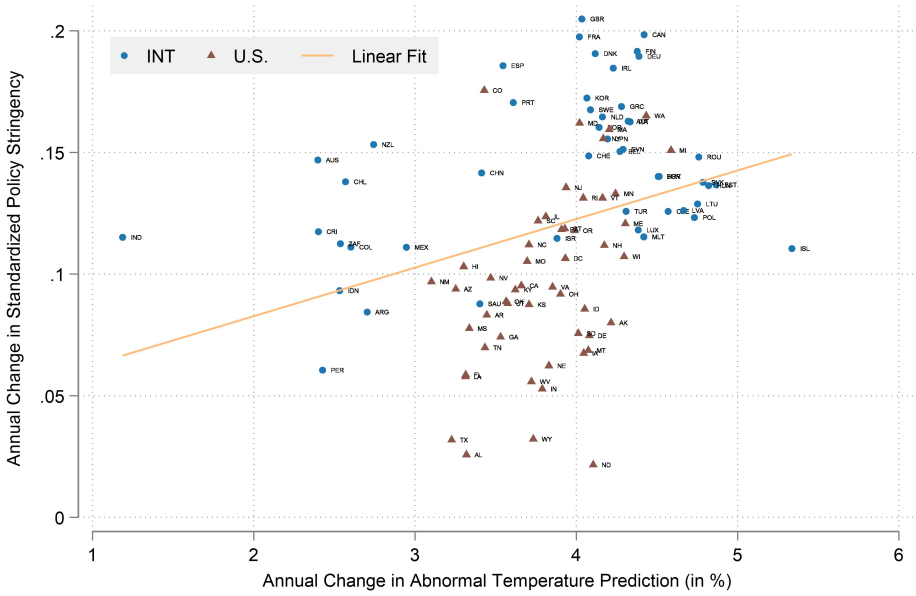



Figure 4: This figure shows the abnormal temperature projected by CMIP3, CMIP5, CMIP6, for the year 2050.

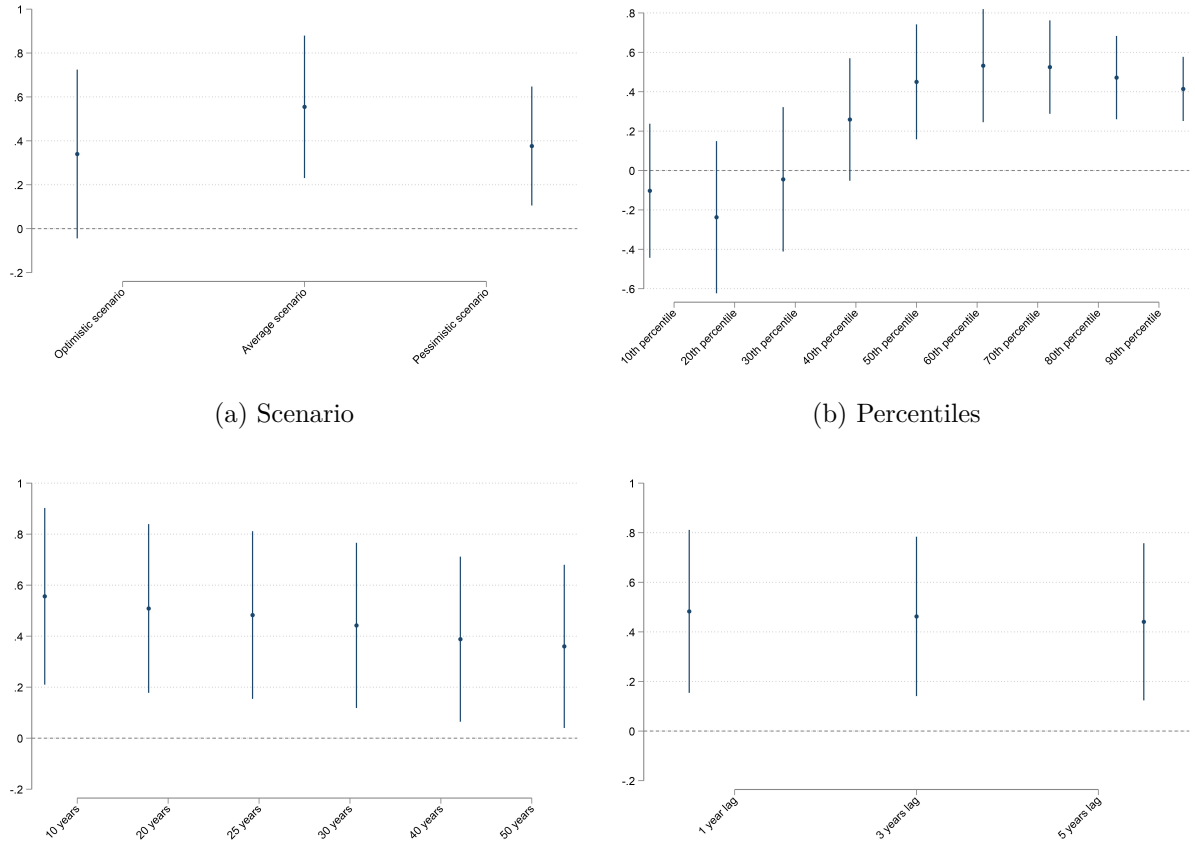



(a) Abnormal temperature predictions and policy stringency




(b) Changes in abnormal temperature predictions and policy stringency

Figure 5: This figure shows the correlation between projected abnormal temperatures and the policy stringency of countries and U.S. states. In Subplot (a), we plot the standardized policy stringency score and the average abnormal temperature prediction per CMIP phase and region. In Subplot (b), we plot the average annual change in the standardized policy stringency score and the average annual percentage change of abnormal temperature projections per region. The solid line shows a linear fit.




(a) Scenario

(b) Percentiles

(c) Forecast horizon

(d) Time lag

Figure 6: This figure shows coefficient estimates for abnormal temperature projections and its 95% confidence interval using the regression specification in Column 3 of Table 2 as baseline model. In Subplot (a), we estimate the model for different climate projection scenarios (optimistic, average, pessimistic). In Subplot (b), we estimate use percentiles of the abnormal temperature projections instead of the average projection in our baseline model. In Subplot (c), we use alternative forecast horizons (baseline: 25 years) and in Subplot (d), we vary the buffer period between the sample year and the start of the forecast period (baseline: one year).

Table 1: Descriptive statistics

| Variable | N | entities | mean | p25 | p50 | p75 | SD |
|---|---|---|---|---|---|---|---|
| *Region-level variables* | | | | | | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ | 1,680 | 99 | 1.56 | 1.25 | 1.48 | 1.79 | 0.419 |
| Abn Temp SD$_{r,t}^{t+1/t+26}$ | 1,680 | 99 | 1.66 | 1.33 | 1.75 | 1.98 | 0.499 |
| Belief$_r$ | 99 | 99 | 0.508 | 0.438 | 0.500 | 0.566 | 0.123 |
| Log(GDP per Capita)$_{r,t}$ | 1,680 | 99 | 10.4 | 9.95 | 10.7 | 10.9 | 0.815 |
| Abn Temp$_{r,t}^{t-2/t}$ | 1,680 | 99 | 0.736 | 0.269 | 0.822 | 1.25 | 0.826 |
| Stringency$_{r,t}$ | 1,680 | 99 | 0 | -0.782 | -0.0734 | 0.654 | 1 |
| Stringency$_{r,t}$: Cross-sectoral | 864 | 48 | 1.85 | 0.222 | 1.52 | 2.96 | 1.76 |
| Stringency$_{r,t}$: International | 864 | 48 | 3.79 | 2.59 | 3.18 | 4.91 | 1.72 |
| Stringency$_{r,t}$: Sectoral | 864 | 48 | 2.57 | 1.64 | 2.59 | 3.44 | 1.21 |
| Readiness$_{r,t}$ | 864 | 48 | 0.551 | 0.440 | 0.536 | 0.687 | 0.144 |
| Readiness$_{r,t}$: Economics | 864 | 48 | 0.543 | 0.437 | 0.542 | 0.649 | 0.132 |
| Readiness$_{r,t}$: Governance | 846 | 47 | 0.624 | 0.441 | 0.601 | 0.828 | 0.213 |
| Readiness$_{r,t}$: Social | 864 | 48 | 0.489 | 0.384 | 0.478 | 0.616 | 0.154 |
| Log CO2$_{r,t}$ (INT, US) | 1,680 | 99 | 4.42 | 3.67 | 4.36 | 5.27 | 1.41 |
| Log GHG$_{r,t+1}$ (INT) | 864 | 48 | 4.89 | 4.01 | 4.70 | 6.27 | 1.66 |
| *Policymaker-level variables* | | | | | | | |
| LCV Score$_{i,t}$ | 10,699 | 1,351 | 49.8 | 6 | 46 | 95 | 42.9 |
| Age$_{i,t}$ | 10,764 | 1,356 | 58.9 | 51 | 59 | 67 | 11 |
| Female$_i$ | 1,356 | 1,356 | 0.214 | 0 | 0 | 0 | 0.41 |
| Edu Score$_i$ | 1,355 | 1,355 | 2.75 | 2 | 3 | 3 | 0.596 |
| Ivy League$_i$ | 1,332 | 1,332 | 0.156 | 0 | 0 | 0 | 0.363 |
| Historical Score$_i$ | 534 | 534 | 45.7 | 5.0 | 35.5 | 91.4 | 40.4 |
| Historical Score 50$_i$ | 534 | 534 | 0.472 | 0 | 0 | 1 | 0.5 |
| Democrat$_i$ | 1,356 | 1,356 | 0.455 | 0 | 0 | 1 | 0.498 |
| Senate$_{i,t}$ | 10,764 | 1,356 | 0.164 | 0 | 0 | 0 | 0.371 |
| Tweet IPCC$_i$ | 770 | 770 | 0.264 | 0 | 0 | 1 | 0.441 |
| Belief Tweet$_i$ | 709 | 709 | 0.814 | -1 | 1 | 2 | 1.45 |
| Belief Wiki$_i$ | 1,011 | 1,011 | 0.294 | -1 | 1 | 1 | 1.31 |
| Belief Tweet Wiki$_i$ | 827 | 827 | 0.661 | -1 | 1 | 2 | 1.49 |

This table presents descriptive statistics. Reported are the number of observations (N), number of unique entities (regions or policymakers), mean value, p25, p50, p75, and standard deviation (SD). The index $r$ indicates aregions, $t$ indicates years, $i$ indicates policymakers. A detailed description of all variables can be found in Appendix A.

Table 2: Temperature projections and policy stringency

**Panel A: Combined sample**

| | Stringency$_{r,t+1}$ | | | |
|---|---|---|---|---|
| Column | (1) | (2) | (3) | (4) |
| Abn Temp$_{r,t}^{t+1/t+26}$ | 1.17*** | 0.94*** | 0.48*** | 0.44*** |
| | (8.49) | (6.93) | (2.92) | (2.71) |
| Log(GDP per Capita)$_{r,t}$ | | 0.29*** | | -0.92*** |
| | | (4.47) | | (-2.73) |
| Abn Temp$_{r,t}^{t-2/t}$ | | 0.21** | | 0.024 |
| | | (2.26) | | (0.88) |
| Year/Region FE | no | no | yes | yes |
| Observations | 1,581 | 1,581 | 1,581 | 1,581 |
| Regions | 99 | 99 | 99 | 99 |
| Adj. $R^2$ | 0.21 | 0.29 | 0.031 | 0.089 |

**Panel B: International and U.S. sample**

| | Stringency$_{r,t+1}$ (INT) | | Stringency$_{r,t+1}$ (U.S.) | |
|---|---|---|---|---|
| Column | (1) | (2) | (3) | (4) |
| Abn Temp$_{r,t}^{t+1/t+26}$ | 0.45*** | 0.41*** | 0.61** | 0.61** |
| | (2.76) | (2.78) | (2.49) | (2.50) |
| Log(GDP per Capita)$_{r,t}$ | | -0.59** | | -0.13 |
| | | (-2.24) | | (-0.23) |
| Abn Temp$_{r,t}^{t-2/t}$ | | -0.021 | | -0.0097 |
| | | (-0.57) | | (-0.31) |
| Year/Region FE | yes | yes | yes | yes |
| Observations | 816 | 816 | 765 | 765 |
| Regions | 48 | 48 | 51 | 51 |
| Adj. $R^2$ | 0.065 | 0.12 | 0.044 | 0.043 |

*continued on next page*

Table 2 continued

The dependent variable is the standardized policy stringency index in year $t+1$ and region $r$. The key independent variable is Abn $\text{Temp}_{r,t}^{t+1/t+26}$, which is the average abnormal temperature projection across all different models and scenarios of the CMIP phase that corresponds to year $t+1$ (see Appendix D) in region $r$ and year $t$ for the period of $t+1$ to $t+26$; the abnormal temperature is calculated relative to the model-specific baseline period from 1900 to 1999. In Panel A, we combine the international and the U.S. sample, while Panel B shows the results for both samples separately. T-statistics based on robust standard errors clustered by regions are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 3: Alternative specifications

| Alternative specification description | Coefficient | t-val |
|---|---|---|
| Baseline | 0.48*** | (2.92) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: Optimistic Scenarios | 0.34** | (1.76) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: Average Scenarios | 0.55** | (3.39) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: Pessimistic Scenarios | 0.38** | (2.76) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 10th Percentile | -0.10 | (-0.60) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 20th Percentile | -0.24 | (-1.22) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 30th Percentile | -0.045 | (-0.24) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 40th Percentile | 0.26 | (1.65) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 50th Percentile | 0.45*** | (3.06) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 60th Percentile | 0.53*** | (3.68) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 70th Percentile | 0.53*** | (4.39) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 80th Percentile | 0.47*** | (4.43) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$: 90th Percentile | 0.41*** | (5.05) |
| Abn $\text{Temp}_{r,t}^{t+1/t+11}$ | 0.56*** | (3.19) |
| Abn $\text{Temp}_{r,t}^{t+1/t+21}$ | 0.51*** | (3.05) |
| Abn $\text{Temp}_{r,t}^{t+1/t+31}$ | 0.44*** | (2.71) |
| Abn $\text{Temp}_{r,t}^{t+1/t+41}$ | 0.39** | (2.38) |
| Abn $\text{Temp}_{r,t}^{t+1/t+51}$ | 0.36** | (2.23) |
| Log(Abn $\text{Temp}_{r,t}^{t+1/t+26}$) | 1.54*** | (5.14) |
| $\text{Stringency}_{r,t}$ | 0.36** | (2.27) |
| $\text{Stringency}_{r,t+2}$ | 0.63*** | (3.41) |
| Stringency (Module 1 blocks average) | 0.47*** | (2.71) |
| SEs clustered by region and year | 0.48** | (2.25) |

This table shows, for various alternative specifications, the coefficient estimates and $t$-statistics for the abnormal temperature variable. The baseline model specifications follows Column (3) in Table 2. T-statistics based on robust standard errors clustered by regions are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 4: Disaggregating climate policies by type

| **Panel A: Policy types** | | | | |
|---|---|---|---|---|
| | Overall Stringency | Sectoral | Cross-sectoral | International |
| Column | (1) | (2) | (3) | (4) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$ | 0.62*** | 0.44* | 0.20 | 1.42*** |
| | (2.76) | (1.81) | (0.49) | (5.24) |
| Year/Region FE | yes | yes | yes | yes |
| Observations | 816 | 816 | 816 | 816 |
| Regions | 48 | 48 | 48 | 48 |
| Adj $R^2$ | 0.065 | 0.034 | 0.00066 | 0.14 |
| **Panel B: Adaptation readiness** | | | | |
| | Overall Readiness | Economic | Governance | Social |
| Column | (1) | (2) | (3) | (4) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$ | 0.041* | 0.13** | 0.036 | -0.049* |
| | (1.79) | (2.19) | (1.13) | (-1.83) |
| Year/Region FE | yes | yes | yes | yes |
| Observations | 864 | 864 | 846 | 864 |
| Regions | 48 | 48 | 48 | 48 |
| Adj $R^2$ | 0.032 | 0.060 | 0.016 | 0.030 |
| **Panel C: Emissions** | | | | |
| | Log $\text{CO2}_{r,t+1}$ (INT, US) | | Log $\text{GHG}_{r,t+1}$ (INT) | |
| Column | (1) | (2) | (3) | (4) |
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$ | -0.26*** | -0.25*** | -0.29*** | -0.25*** |
| | (-3.35) | (-3.46) | (-3.72) | (-3.63) |
| $\text{Log(GDP per Capita)}_{r,t}$ | | 0.45*** | | 0.53*** |
| | | (3.86) | | (4.51) |
| Abn $\text{Temp}_{r,t}^{t-2/t}$ | | -0.0072 | | -0.028* |
| | | (-0.71) | | (-1.71) |
| Year/Region | yes | yes | yes | yes |
| Observations | 1,680 | 1,680 | 864 | 864 |
| Regions | 99 | 99 | 48 | 48 |
| Adj $R^2$ | 0.081 | 0.20 | 0.12 | 0.33 |

*continued on next page*

Table 4 continued

In Panel A, we use the international sample to investigate how abnormal temperature projections affect the different policy types in the CAPMF. The dependent variable is the overall policy stringency index (in contrast to our main analysis, we use the non-standardized version here), as well as the corresponding sectoral, cross-sectoral, and international policy stringency index components in year $t+1$ and region $r$. In Panel B, we use the international sample to investigate how abnormal temperature projections affect countries' adaption readiness. The dependent variables are the overall readiness measures as well as the corresponding economic, governance, and social readiness components in year $t+1$ and region $r$. We restrict this analysis to those countries that are included in our main regressions. In Panel C, we investigate how abnormal temperature projections affect emissions. The dependent variables are Log $CO_2$ emissions in U.S. States and countries in year $t+1$ in Columns (1) and (2) and Log GHG emissions in countries in year $t+1$ in Columns (3) and (4). T-statistics based on robust standard errors clustered by regions are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 5: The role of projection uncertainty

| | $\text{Stringency}_{r,t+1}$ | | | |
|---|---|---|---|---|
| Column | (1) | (2) | (3) | (4) |
| $\text{Abn Temp}_{r,t}^{t+1/t+26}$ | 1.41*** | 1.25*** | 1.24*** | 2.96*** |
| | (4.71) | (4.14) | (4.12) | (4.18) |
| $\text{Abn Temp SD}_{r,t+1/t+26}$ | 0.29 | 0.31 | 0.32 | 0.66 |
| | (0.60) | (0.67) | (0.69) | (1.58) |
| Abn Temp × Abn Temp SD | -0.63*** | -0.55*** | -0.55*** | -0.51*** |
| | (-3.18) | (-2.87) | (-2.85) | (-2.73) |
| $\text{Log(GDP per Capita)}_{r,t}$ | | -0.80*** | -0.79*** | -0.87*** |
| | | (-2.70) | (-2.67) | (-2.90) |
| $\text{Abn Temp}_{r,t}^{t-2/t}$ | | | 0.025 | -0.033 |
| | | | (1.00) | (-1.14) |
| Year/Region | yes | yes | yes | yes |
| Abn Temp × Controls | no | no | no | yes |
| Observations | 1,581 | 1,581 | 1,581 | 1,581 |
| Regions | 99 | 99 | 99 | 99 |
| Adj. $R^2$ | 0.094 | 0.140 | 0.140 | 0.190 |

The dependent variable is the standardized policy stringency index in year $t+1$ and region $r$. The key independent variable is $\text{Abn Temp SD}_{r,t}^{t+1/t+26}$, which is the average standard deviation of monthly abnormal temperature projections across models and scenarios of the CMIP phase that corresponds to year $t+1$ (see Appendix D) in region $r$ and year $t$ for the period of $t+1$ to $t+26$. Interacted continuous variables are centered. T-statistics based on robust standard errors clustered by regions are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 6: The role of climate change belief

| | Stringency$_{r,t+1}$ | | | |
|---|---|---|---|---|
| Column | (1) | (2) | (3) | (4) |
| Abn Temp$_{r,t}^{t+1/t+26}$ | 0.59*** | 0.53*** | 0.53*** | 2.60*** |
| | (3.47) | (3.33) | (3.31) | (3.46) |
| Belief$_r$ | n/a | n/a | n/a | n/a |
| Abn Temp × Belief$_r$ | 1.65*** | 1.31** | 1.31** | 1.25** |
| | (2.91) | (2.39) | (2.38) | (2.31) |
| Log(GDP per Capita)$_{r,t}$ | | -0.78** | -0.77** | -0.87** |
| | | (-2.15) | (-2.13) | (-2.51) |
| Abn Temp$_{r,t}^{t-2/t}$ | | | 0.021 | -0.034 |
| | | | (0.78) | (-1.14) |
| Year/Region | yes | yes | yes | yes |
| Abn Temp × Controls | no | no | no | yes |
| Observations | 1,581 | 1,581 | 1,581 | 1,581 |
| Regions | 99 | 99 | 99 | 99 |
| Adj. $R^2$ | 0.079 | 0.120 | 0.120 | 0.170 |

The dependent variable is the standardized policy stringency index in year $t+1$ and region $r$. The key independent variable is Belief$_r$, which is the percentage of people who believe in climate change in region $r$. Interacted continuous variables are centered. T-statistics based on robust standard errors clustered by regions are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

Table 7: Policymakers' characteristics and their voting behavior

**Panel A: Age, gender, and education**

| | LCV Score$_{i,t+1}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Age$_{i,t}$ | 0.080 | | | |
| | (1.57) | | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Female$_i$ | | 0.061 | | |
| | | (0.047) | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Edu Score$_i$ | | | 0.86 | |
| | | | (0.67) | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Ivy League$_i$ | | | | -0.31 |
| | | | | (-0.26) |
| Year × Region FE | yes | yes | yes | yes |
| Person FE | yes | yes | yes | yes |
| Observations | 9,071 | 9,071 | 9,069 | 8,851 |
| Adj. $R^2$ | 0.00039 | -0.00014 | 0.00007 | -0.00013 |

**Panel B: Past voting, party affiliation, chamber**

| | LCV Score$_{i,t+1}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Historical Score$_i$ | 0.055* | | | |
| | (1.73) | | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Historical Score 50$_i$ | | 4.99* | | |
| | | (1.98) | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Democrat$_i$ | | | 8.88*** | |
| | | | (4.03) | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Senate$_i$ | | | | -1.92 |
| | | | | (-1.60) |
| Year × Region FE | yes | yes | yes | yes |
| Person FE | yes | yes | yes | yes |
| Observations | 4,415 | 4,415 | 9,071 | 9,071 |
| Adj. $R^2$ | 0.0017 | 0.0020 | 0.0120 | 0.00040 |
| R-squared | 0.953 | 0.953 | 0.968 | 0.968 |

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Table 7 continued

**Panel C: Climate belief**

| | LCV Score$_{i,t+1}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Tweet IPCC$_i$ | 3.46* | | | |
| | (1.80) | | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Belief Tweet$_i$ | | 1.77*** | | |
| | | (4.50) | | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Belief Wiki$_i$ | | | 1.46*** | |
| | | | (3.39) | |
| Abn Temp$_{r,t}^{t+1/t+26}$ × Belief Tweet Wiki$_i$ | | | | 2.06*** |
| | | | | (4.66) |
| Year × Region FE | yes | yes | yes | yes |
| Person FE | yes | yes | yes | yes |
| Observations | 6,935 | 6,338 | 7,429 | 7,021 |
| Adj. $R^2$ | 0.0033 | 0.0064 | 0.0028 | 0.0082 |

The dependent variable LCV National Environmental Scorecard score for policymaker $i$ in year $t+1$. Each panel focuses on different characteristics of policymaker $i$. T-statistics based on robust standard errors clustered by regions are presented in parentheses. ***, ** and * indicate significance on the 1%-, 5%- and 10%-levels, respectively. A detailed description of all variables can be found in Appendix A.

# Appendix

Appendix A: Definition of variables

| Variable | Description |
|---|---|
| Abn $\text{Temp}_{r,t}^{t+1/t+26}$ | Average abnormal temperature projection across all different models and scenarios of the CMIP phase that corresponds to year $t+1$ (see Appendix D) in region $r$ and year $t$ for the period of $t+1$ to $t+26$; the abnormal temperature is calculated relative to the model-specific baseline period from 1900 to 1999. Source: Own calculation based on CMIP data. |
| Abn Temp $\text{SD}_{r,t}^{t+1/t+26}$ | Average standard deviation of monthly abnormal temperature projections across models and scenarios of the CMIP phase that corresponds to year $t+1$ (see Appendix D) in region $r$ and year $t$ for the period of $t+1$ to $t+26$. Source: Own calculation based on CMIP data. |
| Abn $\text{Temp}_{r,t}^{t-2/t}$ | Average abnormal temperature across all weather stations for region $r$ from year $t-2$ to $t$; the abnormal temperature is calculated relative to the baseline period from 1900 to 1999. Source: Own calculation based on NOAA's GHCN. |
| $\text{Age}_{i,t}$ | Age of policymaker $i$ in year $t$. Source: Own calculation based on date of birth. |
| $\text{Belief}_r$ | Percentage of people who believe in climate change in region $r$. Source: Gallup Analytics, YPCCC. |
| Belief $\text{Tweet}_i$ | Measure for policymaker $i$'s belief in climate change based on the tweets. Range from -2 to 2. Source: Own calculation based on LLM (see Appendix E). |
| Belief Tweet $\text{Wiki}_i$ | Measure for policymaker $i$'s belief in climate change based on the tweets and Wikipedia page. Ranges from -2 to 2. Source: Own calculation based on LLM (see Appendix E). |
| Belief $\text{Wiki}_i$ | Measure for policymaker $i$'s belief in climate change based on the Wikipedia page. Ranges from -2 to 2. Source: Own calculation based on LLM (see Appendix E). |
| $\text{CO2}_{r,t}$ | CO2 emission excluding Land Use, Land-Use Change and Forestry (LULUCF) in Megatons. Source: World Bank, U.S. Energy Information Administration. |
| $\text{Democrat}_i$ | Dummy variable that indicates whether policymaker $i$ is a Democrat. Source: LCV National Environmental Scorecard. |
| Edu $\text{Score}_i$ | Measure for policymaker $i$'s educational background. Equals 1 if the education background is high school or below, 2 for bachelor's degree, 3 for master's degree, and 4 for doctorate degree. Source: Own calculation based on LLM (see Appendix E). |
| $\text{Female}_i$ | Dummy variable that indicates whether policymaker $i$ is female. Source: GovTrack.us. |
| GDP per $\text{Capita}_{r,t}$ | Gross Domestic Product per Capita of region $r$ in year $t$. Source: World Bank, BEA, U.S. Census. |
| Historical $\text{Score}_i$ | Average LCV Score for policymaker $i$ from 2004 to 2005. Source: Own calculation based on LCV National Environmental Scorecard. |

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Appendix A continued

| Variable | Description |
|---|---|
| Historical Score $50_i$ | Dummy variable that indicates whether policymaker $i$'s historical score is above 50. Source: Own calculation based on LCV National Environmental Scorecard. |
| Ivy League$_i$ | Dummy variable that indicates whether policymaker $i$ has a degree from an Ivy League university. Source: Own calculation based on LLM (see Appendix E). |
| LCV Score$_{i,t}$ | National Environmental Scorecard score at the policymaker-year level from 2005 to 2022. Source: LCV National Environmental Scorecard |
| Readiness$_{i,t}$ | Measure for a country's readiness to adapt to climate change. Source: Notre Dame Global Adaptation Initiative |
| Senate$_{i,t}$ | Dummy variable that indicates whether policymaker $i$ is Senator at time $t$. Source: LCV National Environmental Scorecard. |
| Stringency$_{r,t}$ | Normalized measure for climate policy stringency, which is based on the policy stringency of 48 countries from 2005 to 2022 and 50 U.S. states from 2005 to 2020. Before combining the international and U.S. data, we subtract the measure's mean and divide by its standard deviation within both samples. Source: Nachtigall et al. (2024), Bergquist and Warshaw (2023). |
| Tweet IPCC$_i$ | Dummy variable that indicates whether policymaker $i$ has ever tweeted about IPCC-related topics. Source: Own Calculation. |

More details about the variables can be found in the main text.

Appendix B: CMIP modeling groups

| **Name (short)** | **Name (long)** | **Location** |
|---|---|---|
| AS-RCEC | Research Center for Environmental Changes, Academia Sinica Taiwan | China |
| AWI | Alfred Wegener Institute | Germany |
| BCC | Beijing Climate Centre | China |
| BCCR | Bjerknes Centre for Climate Research | Norway |
| BNU | Beijing Normal University | China |
| CAMS | Chinese Academy of Meteorological Sciences | China |
| CAS | Chinese Academy of Sciences | China |
| CCCMa | Canadian Center for Climate Modelling and Analysis | Canada |
| CCCR-IITM | Centre for Climate Change Research / Indian Institute of TropicalMeteorology | India |
| CMCC | Centro Euro-Mediterraneo sui Cambiamenti Climatici | Italy |
| CNRM | Centre National de Recherches Meteorologiques | France |
| CSIRO | Commonwealth Scientific and Industrial Research Organisation | Australia |
| CSIRO-ARCCSS | CSIRO and Australian Research Council Centre of Excellence for Climate System Science | Australia |
| CSIRO-BOM | CSIRO and Bureau of Meteorology | Australia |
| E3SM | National Laboratories Consortium | USA |
| EC Earth | EC-Earth Consortium | Europe |
| FIO | The First Institute of Oceanography, State Oceanic Administration | China |
| FIO-QNLM | First Institute of Oceanography / Pilot National Laboratory for Marine Science and Technology | China |
| GFDL | Geophysical Fluid Dynamics Laboratory | USA |
| HAM | HAMMOZConsortium | Europe |
| INGV | National Institute of Geophysics and Volcanology | Italy |
| INM | Institute for Numerical Mathematics | Russia |
| IPSL | Institut Pierre-Simon Laplace | France |
| LASG | State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics | China |
| LASG-CESS | LASG & Department of Earth System Science, Tsinghua University | China |
| LASG-IAP | LASG and the Institute of Atmospheric Physics | China |

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Appendix B continued

| Name (short) | Name (long) | Location |
|---|---|---|
| MIROC | U of Tokyo / National Institute for Envir. Studies / Japan Agency for Marine-Earth Science and Technology | Japan |
| MOHC | Met Office Hadley Centre | UK |
| MPI | Max Planck Institute for Meteorology | Germany |
| MRI | Meteorological Research Institute | Japan |
| NASA-GISS | Goddard Institute for Space Studies | USA |
| NCAR | National Center for Atmospheric Research | USA |
| NCC | Norwegian Climate Centre | Norway |
| NIMS-KMA | National Institute of Meteorological Sciences / Korea Meteorological Administration | South Korea |
| NOAA | National Oceanic and Atmospheric Administration | USA |
| NOAA-GFDL | Geophysical Fluid Dynamics Laboratory of NOAA | USA |
| NSF-DOE-NCAR | National Science Foundation / National Center for Atmospheric Research | USA |
| NUIST | Nanjing University of Information Science and Technology | China |
| THU | Department of Earth System Science, Tsinghua University | China |
| UA | University of Arizona | USA |
| UB-KMA | University of Bonn / Meteorological Research Institute of the Korea Meteorological Administration | Germany/Korea |
| UKMO | Hadley Centre for Climate Prediction and Research/Met Office | UK |

Information on modeling groups comes from IPCC (2021), pp. 2101-2107 (link), IPCC (2013), pp. 854-866 (link), and IPCC (2007), pp. 597-599 (link). This illustration follows Lin et al. (2025).

Appendix C: CMIP models

| **Phase** | **Modeling group** | **Model** | **Scenarios** | | | |
|---|---|---|---|---|---|---|
| CMIP 6 | CSIRO | ACCESS-CM2 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CSIRO-ARCCSS | ACCESS-ESM1-5 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | AWI | AWI-CM-1-1-MR | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | BCC | BCC-CSM2-MR | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | BCC | BCC-ESM1 | | | SSP370 | |
| CMIP 6 | CAMS | CAMS-CSM1-0 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CCCMa | CANESM5 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CCCMa | CANESM5-1 | SSP126 | | | SSP585 |
| CMIP 6 | CAS | CAS-ESM2-0 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | NCAR | CESM2-WACCM | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | THU | CIESM | SSP126 | SSP245 | | SSP585 |
| CMIP 6 | CMCC | CMCC-CM2-SR5 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CMCC | CMCC-ESM2 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CNRM | CNRM-CM6-1-HR | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CNRM | CNRM-ESM2-1 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | E3SM | E3SM-1-0 | | | | SSP585 |
| CMIP 6 | E3SM | E3SM-1-1 | | | | SSP585 |
| CMIP 6 | E3SM | E3SM-1-1-ECA | | | | SSP585 |
| CMIP 6 | EC Earth | EC-EARTH3 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | EC Earth | EC-EARTH3-CC | | SSP245 | | SSP585 |
| CMIP 6 | EC Earth | EC-EARTH3-VEG | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CAS | FGOALS-F3-L | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CAS | FGOALS-G3 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | FIO-QNLM | FIO-ESM-2-0 | SSP126 | SSP245 | | SSP585 |
| CMIP 6 | NOAA-GFDL | GFDL-ESM4 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | NASA-GISS | GISS-E2-1-G | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | NASA-GISS | GISS-E2-1-H | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | CCCR-IITM | IITM-ESM | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | INM | INM-CM4-8 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | INM | INM-CM5-0 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | IPSL | IPSL-CM5A2-INCA | SSP126 | SSP370 | | |
| CMIP 6 | IPSL | IPSL-CM6A-LR | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | NIMS-KMA | KACE-1-0-G | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | UA | MCM-UA-1-0 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | MIROC | MIROC6 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | HAM | MPI-ESM-1-2-HAM | | | SSP370 | |
| CMIP 6 | MPI | MPI-ESM1-2-HR | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | MPI | MPI-ESM1-2-LR | SSP126 | SSP245 | SSP370 | SSP585 |

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Appendix C continued

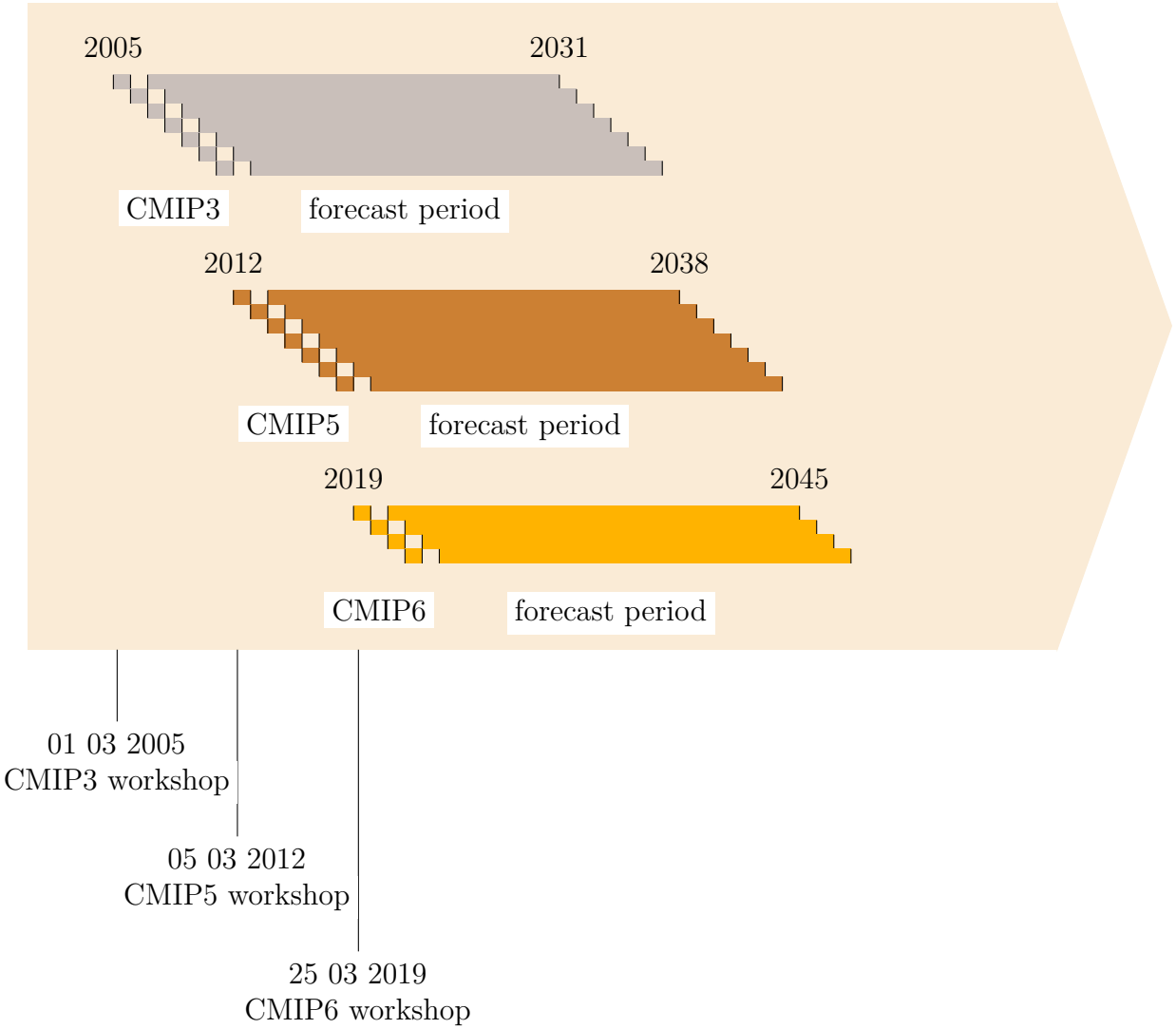
| Phase | Modeling group | Model | Scenarios | | | |
|---|---|---|---|---|---|---|
| CMIP 6 | MRI | MRI-ESM2-0 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | NUIST | NESM3 | SSP126 | SSP245 | | SSP585 |
| CMIP 6 | NCC | NORESM2-LM | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | NCC | NORESM2-MM | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | MOHC | UKESM1-0-LL | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 6 | MOHC | UKESM1-1-LL | SSP126 | | SSP370 | |
| CMIP 6 | MOHC | HadGEM3-GC31 | SSP126 | | | SSP585 |
| CMIP 6 | AS-RCEC | TaiESM1 | SSP126 | SSP245 | SSP370 | SSP585 |
| CMIP 5 | CSIRO-BOM | ACCESS1-0 | | RCP45 | | RCP85 |
| CMIP 5 | CSIRO-BOM | ACCESS1-3 | | RCP45 | | RCP85 |
| CMIP 5 | BCC | BCC-CSM1-1 | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | BCC | BCC-CSM1-1-M | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | BNU | BNU-ESM | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | CCCMa | CANESM2 | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | NCAR | CCSM4 | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NSF-DOE-NCAR | CESM1-BGC | | RCP45 | | |
| CMIP 5 | NSF-DOE-NCAR | CESM1-CAM5 | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NSF-DOE-NCAR | CESM1-WACCM | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | CMCC | CMCC-CESM | | | | RCP85 |
| CMIP 5 | CMCC | CMCC-CM | | RCP45 | | RCP85 |
| CMIP 5 | CMCC | CMCC-CMS | | RCP45 | | RCP85 |
| CMIP 5 | CNRM | CNRM-CM5 | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | CSIRO | CSIRO-MK3-6-0 | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | EC Earth | EC-EARTH | | | | RCP85 |
| CMIP 5 | LASG-CESS | FGOALS-G2 | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | LASG-IAP | FGOALS-S2 | | RCP45 | | RCP85 |
| CMIP 5 | FIO | FIO-ESM | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NOAA | GFDL-CM3 | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NOAA | GFDL-ESM2G | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NOAA | GFDL-ESM2M | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NASA-GISS | GISS-E2-H | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NASA-GISS | GISS-E2-H-CC | | RCP45 | | RCP85 |
| CMIP 5 | NASA-GISS | GISS-E2-R | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NASA-GISS | GISS-E2-R-CC | | RCP45 | | RCP85 |
| CMIP 5 | MOHC | HADGEM2-AO | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | MOHC | HADGEM2-CC | | RCP45 | | RCP85 |
| CMIP 5 | MOHC | HADGEM2-ES | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | INM | INMCM4 | | RCP45 | | RCP85 |
| CMIP 5 | IPSL | IPSL-CM5A-MR | RCP26 | RCP45 | RCP60 | RCP85 |

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Appendix C continued

| Phase | Modeling group | Model | Scenarios | | | |
|---|---|---|---|---|---|---|
| CMIP 5 | IPSL | IPSL-CM5B-LR | | RCP45 | | RCP85 |
| CMIP 5 | MIROC | MIROC-ESM | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | MIROC | MIROC-ESM-CHEM | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | MIROC | MIROC5 | RCP26 | RCP45 | | |
| CMIP 5 | MPI | MPI-ESM-LR | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | MPI | MPI-ESM-MR | RCP26 | RCP45 | | RCP85 |
| CMIP 5 | MRI | MRI-CGCM3 | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | MRI | MRI-ESM1 | | | | RCP85 |
| CMIP 5 | NCC | NORESM1-M | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 5 | NCC | NORESM1-ME | RCP26 | RCP45 | RCP60 | RCP85 |
| CMIP 3 | BCCR | BCCR-BCM20 | A1B | A2 | B1 | |
| CMIP 3 | CCCMA | CCCMA-CGCM31 | A1B | A2 | B1 | |
| CMIP 3 | CNRM | CNRM-CM3 | A1B | A2 | B1 | |
| CMIP 3 | CSIRO | CSIRO-MK30 | A1B | A2 | B1 | |
| CMIP 3 | CSIRO | CSIRO-MK35 | A1B | A2 | B1 | |
| CMIP 3 | GFDL | GFDL-CM20 | A1B | A2 | B1 | |
| CMIP 3 | GFDL | GFDL-CM21 | A1B | A2 | B1 | |
| CMIP 3 | NASA-GISS | GISS-C4X3 | A1B | | B1 | |
| CMIP 3 | NASA-GISS | GISS-E20HYCOM | A1B | | | |
| CMIP 3 | NASA-GISS | GISS-E20RUSSEL | A1B | A2 | B1 | |
| CMIP 3 | LASG | IAP-FGOALS10 | A1B | | B1 | |
| CMIP 3 | INGV | INGV-ECHAM46 | A1B | A2 | | |
| CMIP 3 | INM | INM-INMCM30 | A1B | A2 | B1 | |
| CMIP 3 | IPSL | IPSL-CM4V1 | A1B | A2 | B1 | |
| CMIP 3 | MIROC | MIROC-MIROCV32 | A1B | A2 | B1 | |
| CMIP 3 | UB-KMA | MIUB-ECHOG | A1B | A2 | B1 | |
| CMIP 3 | MPI | MPIM-ECHAM5 | A1B | A2 | B1 | |
| CMIP 3 | MRI | MRI-CGCM232 | A1B | A2 | B1 | |
| CMIP 3 | NCAR | NCAR-CCSM30 | A1B | A2 | B1 | |
| CMIP 3 | NCAR | NCAR-PCM1 | A1B | A2 | | |
| CMIP 3 | UKMO | UKMO-HADCM3 | A1B | A2 | B1 | |
| CMIP 3 | UKMO | UKMO-HADGEM1 | A1B | A2 | | |

Our sample includes CMIP6, CMIP5, and CMIP3 models for which monthly near-surface air temperature (TAS) predictions are available for the following scenarios: SSP126, SSP245, SSP370, SSP585 (CMIP6), RCP26, RCP45, RCP60, RCP85 (CMIP5), and A1B, A2, B1 (CMIP3). Additionally, availability of historical simulation data is required for a model to be included. The data is downloaded as shape files from the Earth System Grid Federation server (CMIP6 link; CMIP5 link; CMIP3 link) and the archive of the German Climate Computing Center (link). Appendix B provides information on the modeling groups. This illustration follows Lin et al. (2025).




Appendix D: This figure provides an overview on the time structure. Our sample starts in 2005 and ends in 2022. For the period from 2005 to 2011, CMIP3 model forecasts are used (2012 to 2018: CMIP5 forecasts; 2019 to 2022: CMIP6 forecasts). The length of the forecast periods is 25 years; the forecast periods starts one year after the end of the respective sample year. We assume that the models of the CMIP phases are publicly available in the year of the corresponding workshop was held. The CMIP3 workshop was held in March 2005 (link), the CMIP5 workshop in March 2012 (link), and the CMIP6 workshop in March 2019 (link). See Lin et al. (2025) for a similar illustration.

Appendix E: LLM based text analysis for policymaker's characteristics

To measure policymakers' characteristics, we use a large language model (LLM) to analyze text from three sources: their official Biographical Directory (Bioguide) webpages, their Wikipedia pages, and their Twitter activity. Among the 1,351 policymakers with LCV scores, we obtain their Bioguide for all of them and Wikipedia pages for 1,310 individuals. In addition, for 706 policymakers, tweets from 2017 to 2023 are available through the Tweets of Congress initiative. Combining these corpora, we then apply the following prompt to extract measures of each policymaker's characteristics.

**Prompt (LLM instruction)**

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You are an expert political science research assistant specializing in biographical data extraction and text analysis. You extract structured data about U.S. policymakers from their Wikipedia pages.You will receive the Wikipedia page **TEXT** of a U.S. policymaker. Your task is to analyze this text and extract information according to the following instructions. You must output the data in a **STRICT JSON** format. Do **NOT** include any conversational text, only the JSON object.

## *Section 1: Education Background*

You must infer and output **aggregated** education information with the following fields:

1. `"education_level"` (string; **ONE** of the following only):
    - `"High School or below"`
    - `"Bachelor"`
    - `"Master"`
    - `"Doctorate or Above"`
    - `"NA"`

    **Rules:**

    - Choose the highest degree obtained as the `education_level`.
    - If they only completed a bachelor's degree (BA, BS, AB, BSc, etc.), use `"Bachelor"`.
    - If they have also completed a JD, MA, MS, MBA, MPA, MPP, MEd, MEng, MSc, etc., or other master-equivalent degrees, use `"Master"`.
    - A Juris Doctor (JD) should be treated as **Master** level for this task.
    - A PhD, DPhil, EdD, MD, DO, DDS, DMD, or other doctoral-level degree → `"Doctorate or Above"`.
    - If the text only indicates attendance but not clear completion, infer cautiously. If unclear, use `"NA"`.
    - If there is no clear education info → `"NA"`.

2. `"education_level_justification"` (string):
    - Briefly explain why you chose that level.
    - Mention specific degrees and institutions, if known.
    - Keep the explanation concise.
3. `"institutions"` (string):
    - A semicolon-separated list (use `"; "` between institutions) of distinct educational institutions attended.
    - Examples: `"Harvard University; University of Texas at Austin; U.S. Naval Academy"`
    - Include universities, colleges, military academies, community colleges, and named high schools if relevant.
    - If multiple campuses of the same university are explicitly named (e.g., "University of California, Berkeley" and "University of California, Los Angeles"), list them separately.
    - If no institution info is available → `"NA"`.

### *Section 2: Climate Change Belief*

Infer the policymaker's belief or stance toward climate change from the text. Consider:

- Statements about whether climate change is real, human-caused, or a serious issue.
- Voting records or policy positions on climate change, environmental regulation, carbon emissions, the Paris Agreement, etc.
- Opposition to climate science, denial of human-caused climate change, or downplaying its importance.

You must produce:

(a) `"climate_belief_score"` (string; one of):
- `"Strongly accepts climate science"`
- `"Generally accepts climate science"`
- `"Mixed or unclear position"`
- `"Generally skeptical of climate science"`
- `"Strongly skeptical or denies climate science"`
- `"NA"`

**Guidelines:**
- `"Strongly accepts climate science"`: Explicitly supports mainstream climate science, emphasizes urgent action, supports strong climate policies, clearly accepts human-caused climate change.

- `"Generally accepts climate science"`: Accepts human-caused climate change and supports some climate policy, but with less emphasis or mixed voting record.
- `"Mixed or unclear position"`: Conflicting statements; or some environmental concern without clear stance on climate science; or different actions at different times.
- `"Generally skeptical of climate science"`: Frequently questions human-caused climate change or downplays severity; but may not fully deny it.
- `"Strongly skeptical or denies climate science"`: Explicitly rejects human-caused climate change or calls it a hoax; strongly opposes climate science consensus.
- `"NA"`: No sufficient information in the text related to climate change, global warming, environment, or related policies.

(b) `"climate_belief_justification"` (string):

- Briefly cite the evidence from the text: quotes, voting behavior, or described policy positions.
- If `"NA"`, state that the text did not provide clear information.
- Keep it concise.

## *Metadata*

Also include:

(a) `"wikipedia_id"` (string):

- The ID of the Wikipedia page, passed to you as context.

## *Output Format (Strict)*

You **MUST** return **ONLY** a JSON object with exactly these keys at the top level:

- `"wikipedia_id"`
- `"education_level"`
- `"education_level_justification"`
- `"institutions"`
- `"climate_belief_score"`
- `"climate_belief_justification"`

All values must be strings.

**Requirements:**

- Use double quotes for all keys and values.

- Do **NOT** include any keys other than those specified.
- Do **NOT** include any text outside the JSON object.
- Keep values single-line (avoid embedded newlines as much as possible).

### *Wikipedia Text to Analyze*

Input Wikipedia ID: `{wikipedia_id}`

Input Text:
`"""` `{text}` `"""`

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