



Political “Color” and the impact of climate risks on output growth: Evidence from a panel of US states

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ABSTRACT

In this paper, we show that the effect of climate risks on economic growth in a panel of 48 contiguous states of the US is contingent on the party affiliation of the local politicians, as captured by a Democratic-Republican Index (DRI). Specifically, our results, based on a regime-dependent local projections model, indicate that extreme weather-related shocks tend to negatively impact output growth more severely, especially in the medium- to long-run, in the Republican-leaning states with low-DRI values compared to those characterized by high-DRI values over the annual period 1967 - 2023. In addition, when we incorporate the information on states that have undertaken explicit targets for reduction of greenhouse gas emissions, following the Climate Change Action Plan implemented in 1993, we find that the significant long-horizon negative effect continues to hold only for the states with low-DRI values, i.e., those that are Republican-oriented.

1. Introduction

In general, it is quite widely believed that compared to the Republicans, Democrats are more apprehensive about climate change (see, for example, Dunlap and McCright [1], McCright and Dunlap [2], Milendenberger et al. [3], Smith et al. [4]).¹ In this regard, a 2023 GALLUP survey indicates that 78 % of Democrats, in contrast to 20 % of Republicans, prioritize environmental conservation over economic considerations, with the partisan division in terms of the perspective on environment being at its historical high.

The critical, and unanswered, question is whether this profound partisan divide translates into materially different economic outcomes

following climate shocks. Against this backdrop, our objective is to empirically verify, for the first-time, whether the, otherwise, well-established negative impact of climate risks on the output growth of states is contingent on their political alignment.² We test the hypothesis that the economic damage in Democrat-leaning states tends to be relatively less pronounced compared to that in Republican ones. This investigation is novel, as it moves beyond documenting partisan beliefs to quantify how political ideology moderates the real economic costs of climate risks. The hypothesis emanates from the evidence that Democrat-leaning states being more concerned about climate change risks, facilitate adoption of effective renewable energy policies, which, in turn, contribute to greater resilience against climate risks [5].

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¹ See also, for example, some important non-academic discussions at: <https://www.pewresearch.org/science/2016/10/04/the-politics-of-climate/>; <https://www.pewresearch.org/short-reads/2020/02/28/more-americans-see-climate-change-as-a-priority-but-democrats-are-much-more-concerned-than-republicans/>; <https://globalaffairs.org/research/public-opinion-survey/republicans-and-democrats-continue-clash-over-climate-change>.

² For detailed reviews involving cross-country studies on the climate risks-growth nexus, see, for example, Donadelli et al. [22], Gupta et al. [23], and Huber et al. [24]. At the same time, recent studies of Colacito et al. [18], Sheng et al. [12], Cepni et al. [25,26] have highlighted the role of US state-level climate risks in reducing economic activity, both for corresponding regions regional and the aggregate economy.

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Moreover, according to Dunlap et al. [6] and McCright et al. [7], Democrats-led states often prioritize policies related to disaster preparedness, environmental protections, and climate change mitigations and adaptations, which can help buffer the negative economic impacts of climate-related risks. Naturally, investments in renewable energy, green technologies and infrastructure, and the adoption of more proactive climate-resilient initiatives and plans, is likely to reduce the long-term vulnerability of these states to climate shocks, leading to quicker recovery or less severe economic downturns, compared to Republican-oriented states.

From an econometric perspective, to test our hypothesis, we utilize the regime-dependent local projections (LPs) model, estimated over the annual sample period of 1967 to 2023 on a panel of 48 neighboring US states, excluding Alaska and Hawaii, due to data availability. Using this framework, we base our inferences on responses of output growth to climate risks shocks under high- and low-values of a Democratic-Republican Index (DRI), which measures the political stance of every state according to the local officials' party affiliation.

Our paper makes several novel contributions to the literature. First, to the best of our knowledge, this is the first study to empirically test whether the economic impact of climate shocks on U.S. state output growth is contingent on the political affiliation of state leadership. Second, moving beyond the simplistic binary "red/blue" categorization of US states, we employ a continuous Democratic-Republican Index

$$\text{PAI} = (1/4) \times \text{Senators} + (1/4) \times \text{Representatives} + (1/4) \times \text{Governor} + 1/4 \times [(1/2) \times \text{State Senators} + (1/2) \times \text{State Representatives}].$$

(DRI) that precisely captures the intensity of a state's political leaning based on the party affiliation of all key elected officials. Third, we uniquely integrate the role of explicit climate policy by examining whether the adoption of Greenhouse Gas (GHG) reduction targets following the 1993 Climate Change Action Plan further moderates these effects.

The sections of the paper are structured as follows: Section 2 discusses the data, while Section 3 presents the empirical framework, with Section 4 investigates the empirical findings, and Section 5 concluding the paper.

2. Data

With regards to the state-level output growth, we use the growth rate of real personal income (GRPI), with nominal level-values obtained from Bureau of Economic Analysis (BEA) and deflated with national Consumer Price Index (CPI), sourced from the FRED database of the Federal Reserve Bank of St. Louis. As far as our measure of extreme weather shock (*Climate Shock*) is concerned, we collect monthly weather data from the National Oceanic and Atmospheric Administration (NOAA) for the 48 US states. The weather data records time-series information on meteorological variables across four key dimensions: temperature (temp), precipitation (precip), heating degree days (hdd), and cooling degree days (cdd).³ In line with the methodology outlined by Choi et al. [8], we break down the weather-related variables into three components that account for seasonal, predictable, and abnormal patterns. Particularly, for each month, t , the monthly weather measure ($W_{i,t}$) for a particular state i is defined by using the following equation: $W_{i,t} = W_{i,t}^M + W_{i,t}^D + W_{i,t}^A$, where $W_{i,t} = \{temp_{i,t}, precip_{i,t}, hdd_{i,t}, cdd_{i,t}\}$, and the term $W_{i,t}^M$ denotes the mean of $W_{i,t}$ for the 10 year period prior to t . Furthermore,

³ The data can be downloaded from: <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/statewide/time-series>.

the variable $W_{i,t}^D$ indicates the difference of the mean of the deviation of $W_{i,t}$ from the monthly average of a particular weather-related variable within the same calendar month for the past decade and $W_{i,t}^M$. Finally, the variable $W_{i,t}^A$ represents the residual component, capturing abnormal deviations in weather conditions. As such, it reflects extreme departures from typical patterns. For this reason, our analysis focuses primarily on this variable. These anomalous deviations are standardized, referred to as the standardized anomaly, to derive the subsequent overall climate risk metric ($CR_{i,t}^{Monthly}$): $CR_{i,t}^{Monthly} = \frac{std(temp_{i,t}^A) + std(precip_{i,t}^A) + std(CDD_{i,t}^A) + std(HDD_{i,t}^A)}{4}$. Having derived the monthly measure of climate risks, as our data is converted to annual ($CR_{i,t}$) by taking a twelve-month average of $CR_{i,t}^{Monthly}$. Then, in line with Engle et al. [9], the climate risks shock series is obtained from the residuals of the autoregressive panel data model of order one, i.e., AR (1), fitted to $CR_{i,t}$.

Motivated by the recent literature on political geography of the states, popularized by Magerakis et al. [10], Kim et al. [11], derives two indexes in this regard namely, the Political Alignment Index (PAI) and the Democratic-Republican Index (DRI).⁴ PAI functions as a metric that assesses the degree of alignment with the political party of the President at the state level, effectively reflecting the presence to political power and hence, depicts policy uncertainty, the important influence of which for state-level output has been highlighted by Baker et al. [28]. The PAI is created using the following formula:

In this formula, "Senators" represents the proportion of the two U.S. Senate members from Washington, D.C., who belong to the same political party as the President. Representatives is the percentage of house members from Washington, D.C that are from the President's party. The governor alignment variable is assigned a value of 1 when the governor and the President belong to the same political party, and 0 if they do not. The state senator's alignment variable is coded as 1 if over half of the state's senators are members of the President's party, and 0 otherwise. Similarly, the state representative's alignment variable takes a value of 1 if >50 % of the state's House representatives are affiliated with the President's party, and 0 otherwise.

The DRI is constructed annually from 1967 to 2023 using party affiliations of state politicians (governor, U.S. senators/representatives, state legislators), weighted identically to the Political Alignment Index (PAI) formula in Kim et al. [11]. The DRI has a scale from 0 to 1. A value of 0 signifies that all politicians in the state are affiliated with the Republican Party, while a value of 1 indicates that all politicians are affiliated with the Democratic Party. This metric reflects the political orientation of the state based on the party affiliations of local politicians. Understandably, the upper (lower)-regime corresponds to states that have relatively higher (lower) DRI values and can be categorized as Democrat (Republican)-leaning or "blue (red)" states. Temporal variation of DRI arises from annual election outcomes and party shifts.

Finally, as national-level controls, following regional analyses involving climate risks and the macroeconomic environment of Sheng et al. [12,13] and Kim et al. [14], we use the CPI-based annual inflation rate, and the effective Federal Funds Rate (FFR), the CPI-deflated nominal West Texas Intermediate (WTI) real oil price log-returns, with

⁴ We extend our gratitude to Professor Jung Chul Park for kindly granting us access to the PAI and DRI datasets.

all raw data obtained from the FRED database. Due to the availability of DRI and PAI data, our annual sample period spans from 1967 to 2023.

3. Methodology

Building on the methodologies proposed by Auerbach and Gorodnichenko [15] and Jordà et al. [16], we utilize a regime-dependent framework to analyze the nonlinear impacts of climate risk shocks on the growth rate of real personal income via Local Projections.⁵ The regimes are determined by the political affiliation of each state, categorized as either predominantly Democrat or Republican. To capture the transition between these regimes, we integrate a logistic smooth transition function into the model, which differentiates between high and low levels of the DRI.⁶ The model is formally expressed as follows⁷:

$$GRPI_{i,t+s} = \alpha_{i,s}^{High} + \beta_s^{High} Climate Shock_{i,t} + \gamma_{t,s}^{High} + \sum_{j=0}^{j=1} \delta_{j,s}^{High} X_{t-j} + \sum_{j=0}^{j=1} \theta_{i,j,s}^{High} PAI_{i,t-j} + F(z_{i,t})$$

$$\left[\left(\alpha_{i,s}^{Low} - \alpha_{i,s}^{High} \right) + \left(\beta_s^{Low} - \beta_s^{High} \right) Climate Shock_{i,t} + \left(\gamma_{t,s}^{Low} - \gamma_{t,s}^{High} \right) + \sum_{j=0}^{j=1} \left(\delta_{j,s}^{Low} - \delta_{j,s}^{High} \right) X_{t-j} + \sum_{j=0}^{j=1} \left(\theta_{i,j,s}^{Low} - \theta_{i,j,s}^{High} \right) PAI_{i,t-j} \right]$$

$$+ \epsilon_{i,t+s}, \text{ for } s = 0, 1, 2, \dots, H$$

$$F(z_{i,t}) = \exp(-\gamma(z_{i,t} - c)) / (1 + \exp(-\gamma(z_{i,t} - c))), \gamma > 0 \quad (2)$$

where $GRPI_{i,t+s}$ represents real personal income growth in the US state i at time t , with s being the forecast horizon.⁸ $z_{i,t}$ is a switching variable capturing the political make-up of the US states based on the party affiliation of the local politicians, as captured by the DRI, and is standardized to have a variance of one and mean of zero. The logistic function $F(z_{i,t})$ serves as a smooth transition function, ranging from 0 to 1.⁹ Values approaching 1 signify the low-DRI regime, while values near 0 indicate the high-DRI regime. Superscripts *High* and *Low* denote the high- and low-DRI regimes, respectively. We consider both the immediate and delayed effects of local policy-related uncertainty, as measured by the state-level political alignment index ($PAI_{i,t}$). We also

⁵ We prefer Local Projections (LP) over Generalized Method of Moments (GMM) and Panel Vector Autoregression (PVAR) because it enables shock-agnostic inference without requiring identifying restrictions [27,17] and offers greater flexibility, accommodating nonlinearities (e.g., regime-switching) and multiple horizons without dynamic misspecification bias [16]. For our analysis, LP's flexibility in accommodating nonlinear dynamics and estimating horizon-specific impulse responses without imposing dynamic restrictions, makes it particularly well-suited for studying persistent and nonlinear effects like those from climate shocks.

⁶ The relationship between the DRI and the effect of climate shocks is nonlinear and captured by the logistic transition function. This allows for a smooth transition between two distinct regimes.

⁷ We have revised the core equation to explicitly show that the climate shock is multiplied by the transition function, making the interaction clear. This is algebraically equivalent to the original model of Auerbach and Gorodnichenko [15] and Jordà et al. [16], which is specified as follow: $GRPI_{i,t+s} = (1 - F(z_{i,t})) \left[\alpha_{i,s}^{High} + \beta_s^{High} Climate Shock_{i,t} + \gamma_{t,s}^{High} + \sum_{j=0}^{j=1} \delta_{j,s}^{High} X_{t-j} + \sum_{j=0}^{j=1} \theta_{i,j,s}^{High} PAI_{i,t-j} \right] + F(z_{i,t}) \left[\alpha_{i,s}^{Low} + \beta_s^{Low} Climate Shock_{i,t} + \gamma_{t,s}^{Low} + \sum_{j=0}^{j=1} \delta_{j,s}^{Low} X_{t-j} + \sum_{j=0}^{j=1} \theta_{i,j,s}^{Low} PAI_{i,t-j} \right] + \epsilon_{i,t+s}$, for $s = 0, 1, 2, \dots, H$.

⁸ In this study, the maximum forecast horizon length, denoted as H , is set to 8, representing an 8-year forecasting period.

⁹ In the logistic smooth transition function, the threshold parameter c is set to 0 as the switching variable is standardized. The parameter γ is set to 1 as a standardizable and practical choice for capturing regime transitions.

control for the national-level variables including inflation rate, monetary policy, and real oil price returns (captured by X_t). The regime-specific coefficient β_s^{High} and β_s^{Low} measures the response of $RGPI_{i,t+s}$ in year $t+s$ to a *Climate Shock* $_{i,t}$ in year t , and the impact is driven by the emergence of the climate risks in the US state i in year t .¹⁰ The local projections-impulse response functions (LPs-IRFs) are computed as a series of regime-specific β_s 's estimated separately for each horizon due to the climate shock.¹¹ Note that, the response of GRPI to contemporaneous and lagged values of the three variables in X and PAI under high- and low-DRI values are captured by the parameter vectors δ and θ , respectively. Unobserved heterogeneity across various US states and time is accounted for, as indicated by the high and low-DRI regimes-based $\alpha_{i,s}$ and $\gamma_{t,s}$. Additionally, individual and time-fixed effects are incorporated into the panel specification.

4. Empirical findings

4.1. Main results

Though the objective is to analyze regime-specific impact of climate risks shocks on the panel of US states, as part of preliminary analysis, we obtained impulse responses from a linear LPs model Jordà [17],¹² to check whether the result observed in the extant literature involving adverse effect of extreme weather shocks on economic growth also holds in our data. As can be seen from Fig. 1, output growth across the US states declines by around 0.5 % immediately following a one-unit climate risks shock. Initially, this shock has a substantial persistent negative impact, but the effect weakens over time and becomes statistically insignificant at around 8-years following the shock.¹³

Previous research has established the adverse effects of climate shocks on economic growth in U.S. states [18,12], primarily driven by declines in labor productivity, capital quality, and research and

¹⁰ We assume that the climate shock is exogenous conditional on the controls. This is consistent with the literature (e.g., [9]) that uses residuals from an AR(1) model as the shock.

¹¹ We outline the step-by-step procedure of our LP approach: Step 1: Estimate the climate shock series as residuals from an AR(1) model. Step 2: Estimate the regime-dependent LP model for each horizon $s = 0, 1, \dots, H$. Step 3: Plot the sequence of estimated coefficients (for each regime) to construct the Impulse Response Functions (IRFs). Step 4: Compute confidence bands based on panel data-corrected standard errors via the delta method.

¹² Formally, the linear LPs model is given as follows: $GRPI_{i,t+s} = \alpha_{i,s} + \beta_s Climate Shock_{i,t} + \gamma_{t,s} + \epsilon_{i,t+s}$, for $s = 0, 1, 2, \dots, H$.

¹³ We conducted a supplementary analysis using the unemployment rate (sourced from FRED, covering 1976–2023) as an alternative indicator of economic performance. Our findings reveal that climate shocks exert a substantial persistent positive impact unemployment rate, which aligns closely with our result that climate shocks reduce output growth. We have also added spatial controls to account for shared shocks affecting multiple states within specific geographic areas in a given year. Specifically, we group states by their respective US Census regions (e.g., Northeast, South, Midwest, West) and include fixed effects for each region-year combination. This approach effectively absorbs common regional disturbances that impact multiple states simultaneously, ensuring these shared dynamics do not confound our estimates of climate risk effects. The results from this specification remain consistent with our core findings. These results are available upon request.

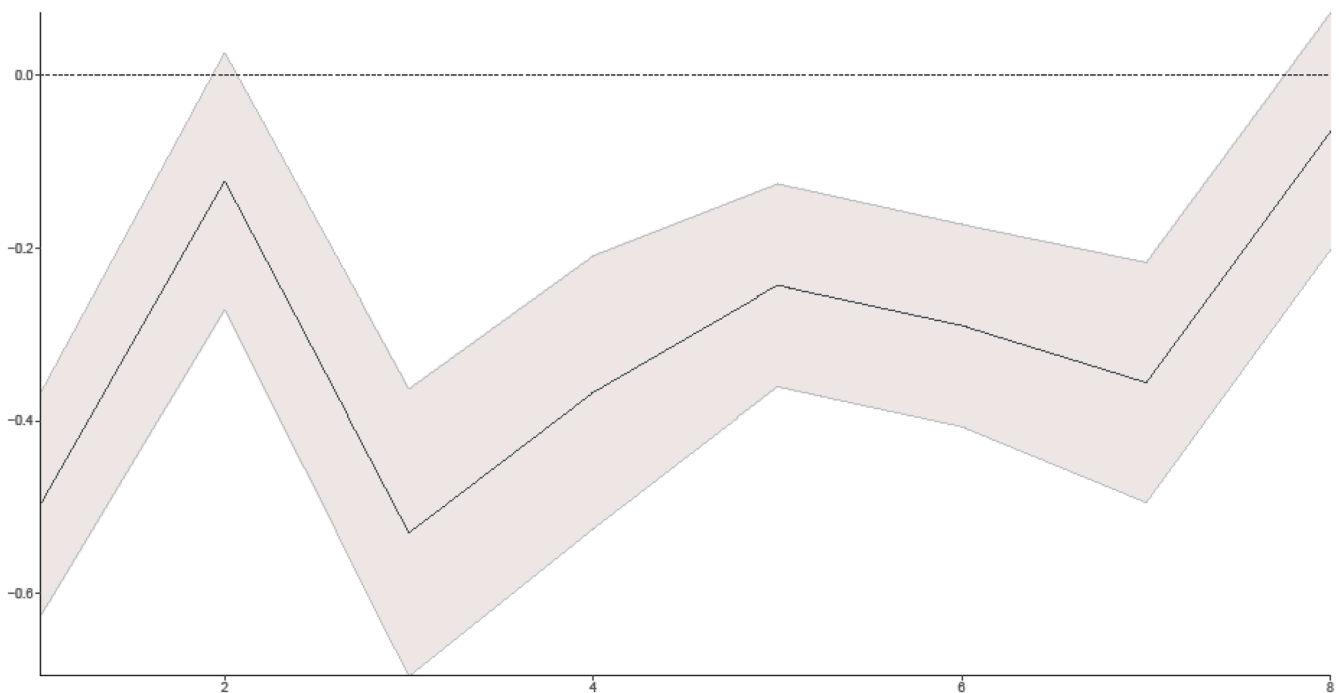


Fig. 1. Linear response of output growth to a shock in climate risks.

Note: The shaded region corresponds to 68 % confidence bands calculated based on panel data-corrected standard errors.

development (R&D) investments [19,20]. Building on these findings, this study shifts its focus to the central objective of the paper: analyzing high- and low-DRI-specific impulse response functions (IRFs).¹⁴

In Fig. 2, we report the regime-specific IRFs from the nonlinear panel model specified in Eqs. (1) and (2), tracking the path of output growth following a shock of one-unit to climate risks. The result from the high DRI regime, corresponding to Democratic-leaning states, is shown on the left-panel, while the IRF from the low-DRI-regime is on the right, and is expected to capture Republican-oriented states.

Fig. 2 shows that in response to a shock to climate risks, output growth in the US states decreases immediately upon impact, regardless of whether they are in high- or low-DRI- regimes, but the subsequent trajectory of the IRFs tends to be quite distinctly different across the two regimes. For the high-DRI-states, one-unit climate risks shocks have a short-term negative impact of about 0.5 % on output growth. However, the effect diminishes rapidly over time, becoming statistically insignificant after three years, suggesting limited medium- to long-run deterioration of economic growth.

In contrast, for the states in the low-DRI regime, the negative growth effect of climate risk shocks is more persistent, covering the 3- to 8-year-ahead period after the shock. While the initial impact of a decline of around 0.4 % due to a one-unit shock is hardly significant, the effect peaks at around the 5-

¹⁴ Theoretically, climate shocks erode output via direct damage (e.g., infrastructure destruction) and indirect Total Factor Productivity (TFP) losses (e.g., disrupted supply chains, health impacts). States differ in adaptive to climate change, determined by e.g., policy investments in resilience (e.g., green infrastructure), institutional quality (e.g., disaster response efficiency), and human capital (e.g., R&D in climate adaptation) etc. High-DRI states prioritize climate action [7], leading to higher public investment in renewables and lower disaster vulnerability. In contrast, low-DRI states underinvest, e.g., due to ideological skepticism. Policy signals from high-DRI states incentivize private adaptation (e.g., firms adopt climate-resistant tech), while low-DRI states face delayed adjustments, amplifying productivity losses. This framework formally establishes how political ideology moderates the impact of climate risk on economic growth, strengthening the paper's contribution to climate-economy-political economy literature.

year-ahead horizon, involving a reduction of >0.7 % of growth. In other words, we observe a delayed, but more prolonged negative impact of climate risks shock on economic growth under the low-DRI-regime. In sum, when we compare Figs. 1 and 2, we can say that the overall persistent impact observed in the linear model originates from high-DRI-states in the short-run, and states characterizing the low-DRI-regime in the medium to long-horizon. More importantly, our regime-specific results tend to provide support to the hypothesis that Democratic-leaning states are likely to have weaker overall effects of climate risks shocks on output growth than those observed under Republican-governance, with relatively faster recoveries possibly arising out of better adaptation initiative in place.¹⁵

The heterogeneous impulse responses across high- and low-DRI regimes may be mediated by institutional features that co-vary with political orientation. In high-DRI states, stricter and more consistently enforced building, land-use, and environmental rules may reduce effective exposure to extreme weather and compress the initial output decline, whereas looser enforcement in low-DRI states might allow greater exposure and contribute to the persistence of adverse effects. Differences in fiscal capacity may also matter, with larger and more resilience-oriented public budgets in high-DRI states supporting pre-disaster hardening and quicker post-disaster disbursement, consistent with the faster reversion seen in their IRFs, while tighter constraints in low-DRI states might be associated with more persistent losses. Variation in administrative capacity and federal-state coordination may further shape outcomes, as specialized staffing, longer planning horizons, and

¹⁵ Using data on Gross Domestic Product (GDP) growth, obtained from the FRED database, and the Actuaries Climate Index (ACI), available at: <https://actuariesclimateindex.org/data/>, we present some additional results in the Appendix involving the overall US economy over the quarterly period of 1961:01 to 2024:01. In Figure A1, we report the time-varying IRFs of growth to the ACI-based climate risks shock, obtained from the time-varying-parameter (TVP)-LPs approach of Inoue et al. [27], and in Figure A2, we report the average of the time-varying responses across the horizons over the periods of Democratic and Republican presidents. Our findings from Figure A1 confirm that GDP growth is adversely affected by climate risks, while Figure A2, in line with Figure 2, highlights that recovery following an ACI shock is faster when Democratic presidents are in office, compared to that under Republican-regimes.

stronger grants management can accelerate policy execution. Because PAI enters the specification, the DRI-linked patterns might reflect structural capacity differences that extend beyond contemporaneous alignment with the federal executive. Taken together, these considerations may provide an institutional interpretation of the nonlinear responses in our regime-dependent local projections framework.

4.2. Additional results

Note that, President William (Bill) J. Clinton announced the Climate Change Action Plan (CCAP) in 1993, as a response to the threat of climate change and to move the US economy toward environmentally sound economic growth via reductions in Green House Gas (GHG) emissions. Given this, as per the US State Climate Action Plans, 24 states¹⁶ have adopted specific GHG reduction targets, as discussed in detail by the Center for Climate and Energy Solutions (C2ES).¹⁷ In this regard, to examine the interplay between political color and actual climate risk management policies, on economic growth, we further extend Equation (1) by creating a climate action plan dummy variable (*CAP*) and interacting it with the climate risks shock as follows:

$$GRPI_{i,t+s} = (1 - F(z_{i,t})) \left[\alpha_{i,s}^{High} + \beta_s^{High} Climate Shock_{i,t} \times CAP_i + \gamma_{t,s}^{High} + \sum_{j=0}^{j=1} \delta_{j,s}^{High} Z_{t-j} + \sum_{j=0}^{j=1} \theta_{i,j,s}^{High} PAI_{i,t-j} \right] + F(z_{i,t}) \left[\alpha_{i,s}^{Low} + \beta_s^{Low} Climate Shock_{i,t} \times CAP_i + \gamma_{t,s}^{Low} + \sum_{j=0}^{j=1} \delta_{j,s}^{Low} Z_{t-j} + \sum_{j=0}^{j=1} \theta_{i,j,s}^{Low} PAI_{i,t-j} \right] +_{i,t+s}, \text{ for } s = 0, 1, 2, \dots, H \tag{3}$$

where the *CAP*_{*i*} takes a value of 1 for the twenty-four US states that have already climate action plans in place and have established Greenhouse gas reduction objectives to combat climate change, with the dummy taking a value of 0 for the other 24 states. Eq. (3) is estimated over the sub-sample of 1993 to 2023.

The expectation is that, in the wake of undertaking such an explicit climate-related policy measure, the negative impact on output should be reduced across both regimes, but less so under the high-DRI-states. And as can be seen from Fig. 3, this is indeed the case, with the effect of the climate risks shock being statistically insignificant under the high-DRI-regime over the entire horizon, though for the low-DRI-states, the adverse effect continues to be statistically significant over the 6- to 8-year-ahead period following the shock. Our findings suggest that while actions undertaken to reduce the impact of climate change does play a role in acting as a buffer against extreme weather shocks for economic growth, the role of the political affiliation of the states cannot be denied, as it is the latter that determines the speed of adoption of climate-related policies.¹⁸ More specifically, policies of reducing

¹⁶ The states are: Washington, Virginia, Vermont, Texas, Rhode Island, Pennsylvania, North Carolina, New York, New Mexico, New Jersey, New Hampshire, Nevada, Montana, Minnesota, Michigan, Massachusetts, Maryland, Maine, Kentucky, Florida, Delaware, Connecticut, Colorado, and California.

¹⁷ See: <https://www.c2es.org/content/state-climate-policy/>.

¹⁸ We split our sample into two key periods: Pre-1993 (1967–1992): A period characterized by the absence of nationwide climate policy. Post-1993 (1993–2023): The era following the introduction of the Climate Change Action Plan (CCAP), a pivotal policy milestone that aimed to coordinate federal efforts on climate adaptation and mitigation. Our sub-period estimates reveal that the divergence in climate resilience driven policy shifts becomes significantly more pronounced in the post-1993 period. This suggests that policy frameworks introduced in or around 1993 may have influenced how regions adapt to climate shocks, amplifying differences in resilience across states.

GHG emissions are found to be more effective in terms of neutralizing adverse effects on economic growth following a climate shock in states that are Democrats-leaning, compared to the Republican-led ones.

The CAP interaction results are consistent with the above-mentioned mechanisms. The CAP dummy captures formal policy commitment, but its ability to attenuate climate-shock effects depends on enforcement, fiscal prioritization, and administrative follow-through. In high-DRI states, stronger monitoring, permitting, and capital budgeting make CAP commitments more binding in practice, rendering the IRFs statistically insignificant across horizons. In low-DRI states, implementation gaps—stemming from weaker enforcement and more limited fiscal/administrative capacity—dampen the effectiveness of CAP, leaving medium- to long-run output effects materially negative. Because PAI is included, these differences plausibly reflect state-level institutions rather than short-run alignment with federal political power.

5. Conclusion

This study examines the varying effects of extreme weather events on economic output growth between U.S. states that predominantly support Republican policies and those that favor Democratic policies over

the period from 1967 to 2023. Given widespread evidence that Democrats are more concerned about climate change than Republicans, we employ regime-dependent impulse responses of output growth following a climate risks shock, with the regimes captured by a Democratic-Republican Index depicting party affiliation of the local politicians. Our results support the hypothesis that political alignment moderates climate impact, especially in the medium- to long-run. Notably, our analysis incorporates data from states that have implemented specific emissions reduction targets under the Climate Change Action Plan introduced in 1993, revealing that the significant long-term negative effects are observed only in states identified as Republican leaning (“red” states).

5.1. Policy implications and relevance

Our findings carry important policy implications, especially regarding the role of bipartisan support in enhancing climate resilience. The evidence that Democratic-leaning states suffer less severe long-run economic damages from climate shocks than Republican-leaning states suggests that proactive climate policies and investments—more commonly adopted in “blue” states—provide a buffer against extreme weather events. Therefore, a key implication is that bridging the partisan divide on climate action could strengthen resilience nationwide. In practice, this means fostering cross-party consensus on climate adaptation and mitigation measures so that all states, regardless of political orientation, implement robust strategies to cope with climate risks.

Climate change does not respect political boundaries, and our results indicate that states with greater commitment to climate initiatives experience quicker recoveries or milder economic downturns after climate shocks. By contrast, states lagging in climate preparedness (often for partisan reasons) face more prolonged growth setbacks. If

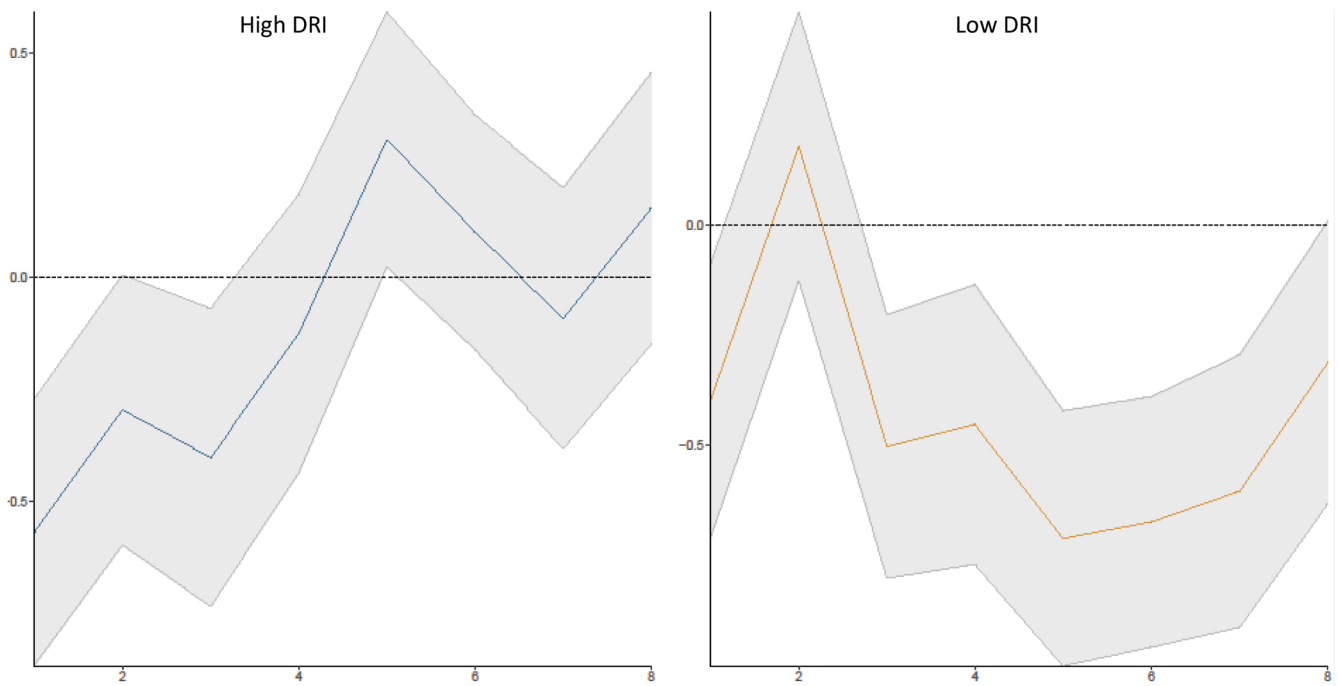


Fig. 2. The nonlinear response of output growth to a shock in climate risks across high- and low-democratic-republican index (DRI) Regimes.
Note: Fig. 2 reports regime-specific IRFs from the nonlinear panel model tracking output growth after a one-unit climate risk shock: the left panel showing IRFs from the high DRI regime and the right panel displaying IRFs from the low DRI regime. The shaded region corresponds to 68 % confidence bands calculated based on panel data-corrected standard errors.

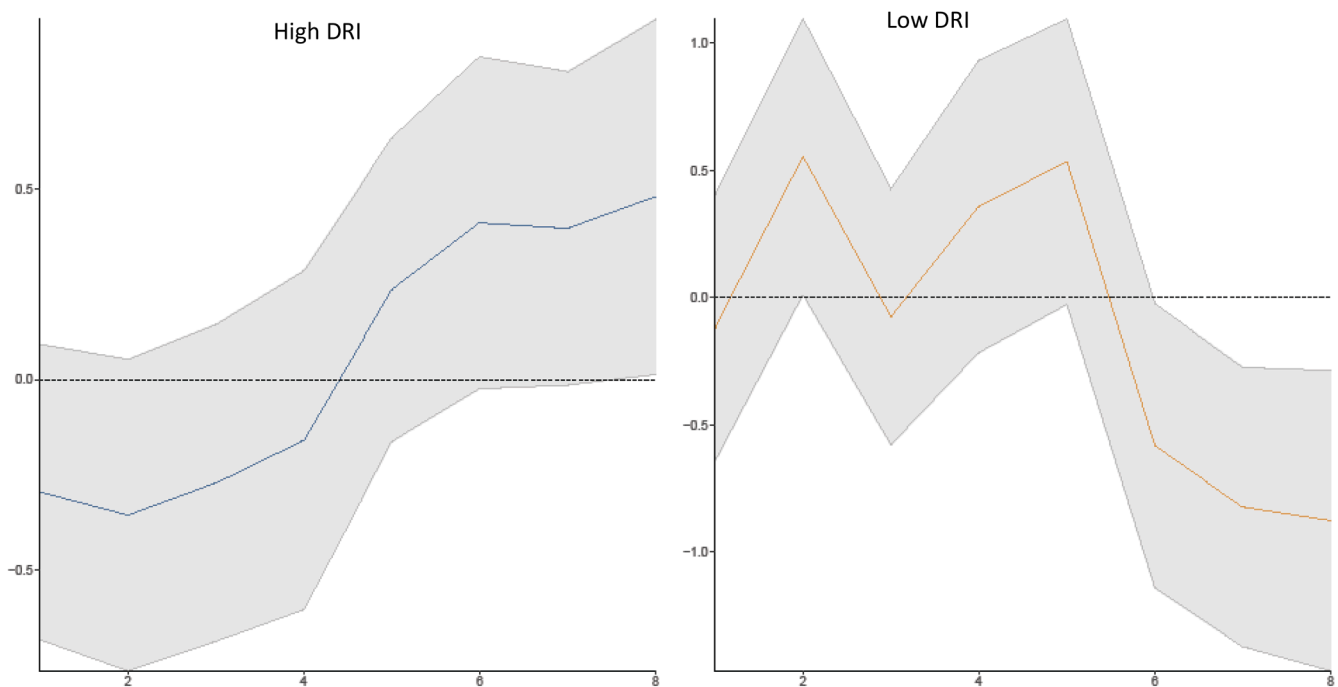


Fig. 3. The nonlinear response of output growth to a shock in climate risks between high- and low-democratic-republican Index (DRI) Regimes Accounting for Climate Change Action Plan of 1993.
Note: The shaded region corresponds to 68 % confidence bands calculated based on panel data-corrected standard errors.

bipartisan cooperation can be achieved on climate policy, these lagging states are more likely to adopt and accelerate resilience-building policies, closing the gap in vulnerability. In other words, bipartisan support for climate initiatives would likely enhance the overall climate resilience of the U.S. economy by ensuring that protective measures – such as investments in green infrastructure, disaster preparedness, and emissions reduction – are implemented uniformly and decisively across the country.

From an empirical standpoint, our study's results imply that if Republican-leaning states were to embrace climate risk mitigation with the same urgency as Democrat-leaning states, the negative impact of extreme weather on output could be substantially reduced across the board. In fact, evidence shows that in politically conservative states, environmental legislation often succeeds only when it attains bipartisan support, reflecting the importance of coalition-building to overcome partisan hurdles [21]. Thus, encouraging bipartisan alliances – for example, through Climate Solutions Caucuses or joint state-federal initiatives – could facilitate the adoption of effective resilience strategies in all states. This would likely diminish the divergent outcomes we observed and promote more uniform economic resilience to climate shocks.

In summary, our findings highlight not just a political divide in climate vulnerability, but also a pathway forward: bipartisan commitment to climate resilience is essential for enhancing long-run economic

growth in the face of climate risks. Policymakers should leverage areas of common ground (such as disaster preparedness, infrastructure safety, or clean energy innovation) where public support transcends party lines. Ultimately, treating climate resilience as a nonpartisan priority would bolster the nation's overall capacity to withstand and bounce back from the increasing incidence of extreme weather, aligning economic stability with prudent environmental stewardship.

CRediT authorship contribution statement

Xin Sheng: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Rangan Gupta:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Data curation, Conceptualization. **Oguzhan Cepni:** Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization. **Masego Motsuenyane:** Writing – review & editing, Writing – original draft, Methodology, Data curation.

Declaration of competing interest

The authors declare no competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Appendix

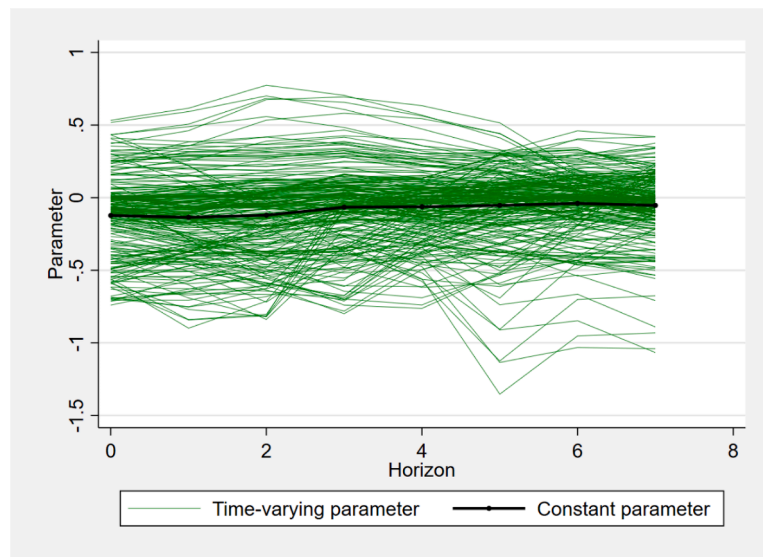


Fig. A1. The Time-Varying Responses of GDP Growth to Climate Risks (Actuaries Climate Index: ACI) Shock.

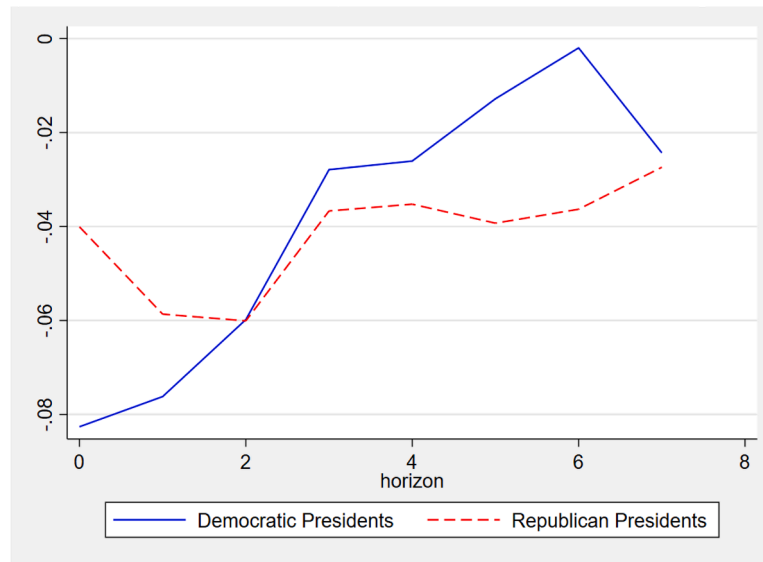


Fig. A2. The Average of Time-Varying Responses of GDP Growth to Climate Risks (Actuaries Climate Index: ACI) Shock across Democratic and Republican Presidents.

Table A1
Variable description and sources.

Variable	Description	Source	Frequency
GRPI	Growth rate of real personal income (state-level output growth)	Bureau of Economic Analysis (BEA) for nominal income; FRED database for CPI	Annual
Climate Shock	Measure of extreme weather anomalies capturing abnormal deviations in temperature, precipitation, heating degree days (HDD), and cooling degree days (CDD)	National Oceanic and Atmospheric Administration (NOAA)	Monthly (aggregated to annual)
PAI (Political Alignment Index)	Measures state-level alignment with the U.S. President’s party, reflecting policy uncertainty	Constructed by authors following Kim et al. [11]; election data	Annual
DRI (Democratic-Republican Index)	Measures state political orientation based on party affiliations of elected officials	Constructed by authors following Kim et al. [11]; election data	Annual
Inflation	National inflation rate	FRED database	Annual
FFR (Federal Funds Rate)	Monetary policy interest rate	FRED database	Annual
Oil Returns	Changes in global energy prices	FRED database	Annual

Data availability

Data will be made available on request.

References

[1] R.E. Dunlap, A.M. McCright, A widening gap: republican and Democratic views on climate change, *Environ.: Sci. Policy Sustain. Dev.* 50 (5) (2008) 26–35.

[2] A.M. McCright, R.E. Dunlap, The politicization of climate change and polarization in the American public’s views of global warming, 2001–2010, *Sociol. Q.* 52 (2) (2011) 155–194.

[3] M. Mildeberger, J.R. Marlon, P.D. Howe, A. Leiserowitz, The spatial distribution of Republican and Democratic climate opinions at state and local scales, *Clim. Change* 145 (3) (2017) 539–548.

[4] E.K. Smith, M.J. Bogner, A.P. Mayer, Polarisation of climate and environmental attitudes in the United States, 1973–2022, *npj Climate Action* 3 (2024). Article No. 2.

[5] M.A. Delmas, M.J. Montes-Sancho, US state policies for renewable energy: context and effectiveness, *Energy policy* 39 (5) (2011) 2273–2288.

[6] R.E. Dunlap, C. Xiao, A.M. McCright, Politics and environment in America: partisan and ideological cleavages in public support for environmentalism, *Env. Polit.* 10 (4) (2001) 23–48.

[7] A.M. McCright, C. Xiao, R.E. Dunlap, Political polarization on support for government spending on environmental protection in the USA, 1974–2012, *Soc. Sci. Res.* 48 (2014) 251–260.

[8] D. Choi, Z. Gao, W. Jiang, Attention to global warming, *Rev. Financ. Studies* 33 (3) (2020) 1112–1145.

[9] R.F. Engle, S. Giglio, B. Kelly, H. Lee, J. Stroeberl, Hedging climate change news, *Rev. Financ. Studies* 33 (3) (2020) 1184–1216.

[10] E. Magerakis, C. Pantzalis, J.C. Park, The effect of proximity to political power on corporate cash policy, *J. Corpor. Finance* 82 (2023) 102448.

[11] C.(F.). Kim, C. Pantzalis, J.C. Park, Political geography and stock returns: the value and risk implications of proximity to political power, *J. Financ. Econ.* 106 (2012) 196–228.

[12] X. Sheng, R. Gupta, O. Cepni, The effects of climate risks on economic activity in a panel of US states: the role of uncertainty, *Econ. Lett.* 213 (2022) 110374.

[13] X. Sheng, R. Gupta, O. Cepni, Persistence of state-level uncertainty of the United States: the role of climate risks, *Econ. Lett.* 215 (2022) 110500.

[14] Kim, H.S., Matthes, C., and Phan, T. 2025. (Forthcoming). Severe Weather and the Macroeconomy. *American Economic Journal: Macroeconomics*. Available at: <https://www.aeaweb.org/articles?id=10.1257/mac.20220329>.

[15] A.J. Auerbach, Y. Gorodnichenko, Fiscal multipliers in recession and expansion. National Bureau of Economic Research (NBER) chapters. *Fiscal Policy after the Financial Crisis*, NBER, Inc, Cambridge, Massachusetts, United States, 2012, pp. 63–98.

[16] O. Jordà, M. Schularick, A.M. Taylor, The effects of quasi-random monetary experiments, *J. Monet. Econ.* 112 (2020) 22–40.

[17] O. Jordà, Estimation and inference of impulse responses by local projections, *Am. Econ. Rev.* 95 (1) (2005) 161–182.

[18] R. Colacito, B. Hoffmann, T. Phan, Temperature and growth: a panel analysis of the United States, *J. Money, Credit Bank.* 51 (2–3) (2019) 313–368.

[19] W. Liao, X. Sheng, R. Gupta, S. Karmakar, Extreme weather shocks and State-level inflation of the United States, *Econ. Lett.* 238 (2024) 111714.

- [20] X. Sheng, R. Gupta, O. Cepni, Time-varying effects of extreme weather shocks on output growth of the United States, *Financ. Res. Lett.* 70 (2024) 106318.
- [21] R. Marshall, M.G. Burgess, Advancing bipartisan decarbonization policies: lessons from state-level successes and failures, *Clim. Change* 171 (1) (2022) 17.
- [22] M. Donadelli, M. Jüppner, S. Vergalli, Temperature variability and the macroeconomy: a world tour, *Environ. Resour. Econ.* 83 (2022) 221–259.
- [23] R. Gupta, J. Nel, A.A. Salisu, Q. Ji, Predictability of economic slowdowns in advanced countries over eight centuries: the role of climate risks, *Financ. Res. Lett.* 54 (2023) 103795.
- [24] F. Huber, T. Krisztin, M. Pfarrhofer, A Bayesian panel VAR model to analyze the impact of climate change on high-income economies, *Ann. Appl. Statist.* 17 (2) (2023) 1543–1573.
- [25] O. Cepni, C. Christou, R. Gupta, Forecasting national recessions of the United States with state-level climate risks: evidence from model averaging in Markov-switching models, *Econ. Lett.* 227 (2023) 111121.
- [26] C. Cepni, R. Gupta, W. Liao, J. Ma, Climate risks and forecastability of the weekly state-level economic conditions of the United States, *Int. Rev. Finance* 24 (1) (2024) 154–162.
- [27] A. Inoue, B. Rossi, Y. Wang, Local projections in unstable environments, *J. Econom.* (2024), <https://doi.org/10.1016/j.jeconom.2024.105726>.
- [28] S.R. Baker, S.J. Davis, J.A. Levy, State-level economic policy uncertainty, *J. Monet. Econ.* 132 (C) (2022) 81–99.