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The Effects of Uncertainty on Economic Conditions across US States: The Role of Climate Risks

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Abstract

We analyse the impact of uncertainty on the Economic Conditions Index (ECI) of the 50 US states in a panel data set-up, over the weekly period of the 3rd week of April 1987 to the 4th week of March 2023. Using impulse response functions (IRFs) from a linear local projections (LP) model, we show that uncertainty, as captured by the stochastic volatility (SV) of the ECIs, negatively impacts ECI in a statistically significant manner. More importantly, using a nonlinear LP model, the IRFs reveal that the adverse effect of uncertainty is significantly much stronger under the high-regime of climate risks when compared to the low-regime of the same. Understandably, our results have important policy implications.

Keywords: Economic conditions; Uncertainty; Climate risks; US states; Linear and nonlinear local projections models

JEL Codes: C23, D80, E32, Q54.

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1. Introduction

Higher uncertainty, as observed due to the Global Financial Crisis of 2007-2009, and the outbreak of the COVID-19 pandemic in 2020, has been shown to adversely impact the state-level economic activity of the United States (US; see, for example, Shoag and Veuger (2016), Mumtaz (2018), Mumtaz et al. (2018), Baker et al. (2022), Hankins et al. (2022), Elkamhi et al. (2023)). Theoretically, this is because, economic uncertainty negatively affects the aggregate demand of the economy through the traditional channel associated with the real option theory as outlined in Bernanke (1983), and more recently, by Bloom (2009, 2014). This theory suggests that decision-making is affected by uncertainty because it raises the option value of waiting. In other words, given that the costs associated with wrong investment decisions are very high, uncertainty makes firms and, in the case of durable goods, also consumers, more cautious. As a result, economic agents postpone investment, hiring, and consumption decisions to periods of lower uncertainty. At the same time, uncertainty is also expected to have a negative effect on the supply side of the economy through lower productivity due to the misallocation of factors across firms (Bloom et al., 2018). According to Bloom et al. (2018), unproductive firms contract and productive firms expand during normal times, which, in turn, helps to maintain high levels of aggregate productivity. But when uncertainty is high, firms reduce expansion and contraction, thus shutting off much of this productivity-enhancing reallocation, which ultimately manifests itself as a fall in measured aggregate total factor productivity, and economic activity.

We aim to add to this literature on the regional effects of uncertainty in the US from multiple perspectives. First, unlike the existing studies on the impact of uncertainty singular metrics of state-level real economic activity, such as personal income, real Gross Domestic Product (GDP), or unemployment, we analyze a broad measure of economic conditions as developed by Baumeister et al. (2024). These Economic Conditions Indexes (ECIs) cover multiple dimensions of the state economies involving indicators of mobility, labor market, real economic activity, expectations, financial conditions, and household spending. This is important since the impact of uncertainty is not only restricted to the real side of the economy (Jurado et al., 2015; Ludvigson, 2021; van Eyden et al., 2022). Second, different from the abovementioned regional studies on the uncertainty-economic activity nexus conducted at monthly, quarterly or annual frequencies, and at times even without time-variation, we investigate the effect on the ECI at the weekly level, which, in turn, is the highest possible frequency available for such indicators. Understandably, a high-frequency analysis of state economic conditions contingent on movements in uncertainty, with the latter captured by the corresponding stochastic volatility of the ECI, is likely to be of more importance to policymakers in undertaking appropriate policy decisions in a timely fashion when compared to results based on low-frequency structural analyses. Finally, again for the first time, realizing that climate change is one of the most defining challenges of our time by posing a large multi-dimensional aggregate risk to the macroeconomy and financial markets (Giglio et al., 2021; Stroebel and Wurgler, 2021; van Benthem et al., 2022), we test a hypothesis that, the effect of uncertainty on the ECI across the US states should be contingent on the level of extreme weather-related risks. In particular, the expectation is that the negative effect of uncertainty on the ECI should be exacerbated under a regime of higher climate risks compared to a situation involving lower values of the same.

What we postulate above is derived from two strands of theoretical models involving rare disaster risks and inattention of economic agents. First, based on the modifications to the original models of rare disaster risks (Rietz, 1988; Barro, 2006, 2009), heightened climate risks considered as rare disaster events (Baker et al., 2024), are likely to have a negative influence on economic activity not only through the deterioration of labour productivity and capital quality, but also through the patent obsolescence channel, which in turn, dampens Research and Development (R&D) expenditure growth (Donadelli et al., 2017, 2021a, b, 2022). In other words, climate risks can produce a reduction in economic activity from both the demand- and supply-sides. In this regard, recent empirical studies have confirmed the role of extreme weather risks in reducing narrow and broad measures of state-level economic activity, including the ECI, of the US (see, for instance, Colacito et al. (2019), Sheng et al. (2020a), Cepni et al. (2024)). Second, Sundaresan (2023), motivated by the literature on inattention, developed a model to show that rare disaster risks (as proxied by climate risks) enhance persistence in the process of uncertainty. More specifically, in this model, agents choose whether and how to prepare for different possible states of the world by collecting information, but they also optimally ignore sufficiently unlikely events. Hence, the occurrence of such events does not resolve, but increases, uncertainty. With uncertain agents having dispersed beliefs, uncertainty begets uncertainty, and results in endogenous persistence. The theoretical proposition of Sundaresan (2023) has been empirically confirmed by Sheng et al. (2022b), who showed that extreme climate-related risks can result in enhancing the persistence of economic uncertainties at the state level for the US.

To achieve our objectives econometrically, we rely on the analysis of impulse response functions (IRFs) of the ECIs following a shock to extreme weather shocks based on linear and nonlinear Local Projections (LP) approaches of Jordà (2005), and Gorodnichenko and

Auerbach (2013) and Jordà et al., (2020), respectively, in a panel data-setting of 50 US states over the period of the 3rd week of April 1987 to the 4th week of March 2023. Note that, the nonlinear LP model allows us to obtain climate risks-based-regime-specific responses of the ECI following a positive shock to uncertainty. We utilize the LP method to obtain the relevant IRFs associated with our questions, as it does not require restrictive identification assumptions on the specification and estimation of the unknown true multivariate system itself and, thus, has a distinct advantage over the traditional Vector Autoregression (VAR) approach. Furthermore, the LP model uses simple regression estimation techniques (such as the Ordinary Least Squares (OLS)) and can easily accommodate nonlinear models with flexible specifications, as used to obtain the state- dependent (as defined by levels of extreme weather risks) IRFs for ECI following an uncertainty shock.

To the best of our knowledge, this is the first paper to analyse the effect of uncertainty on an index capturing economic conditions, spanning various sectors of the US states at a high-frequency, and, more importantly, contingent on regimes of climate risks proxying rare disaster events. The remainder of the paper is organized as follows: Section 2 discusses the data used, Section 3 presents the linear and nonlinear econometric models and the associated empirical findings, and Section 4 concludes.

2. Data

Our dependent variable, i.e., the ECIs of the 50 US states, on which we apply the linear and nonlinear LPs methods, to derive climate risks-based-regime-independent and regime-dependent IRFs following an uncertainty shock, is based on the work of Baumeister et al. (2024). These authors derive the indexes from mixed-frequency dynamic factor models (DFMs) with weekly, monthly, and quarterly variables that cover multiple dimensions of the state economies. Specifically, Baumeister et al. (2024) group the underlying variables into six broad categories: mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators.[1] Table 1 in their paper summarizes the state-level data that they use in the construction of the weekly ECIs, and also includes information on the data frequency, source, transformation, seasonal adjustment, and the start date of each series. The indexes are scaled to 4-quarter growth rates of US real GDP and normalized such that a value of zero indicates national long-run growth.

[1] The data can be downloaded from: https://sites.google.com/view/weeklystateindexes/dashboard.

It is important to emphasize that uncertainty is a latent variable, and hence, one requires ways to measure it. In this regard, at the state level, uncertainty has been quantified using a newspapers-based by Baker et al. (2022) and Elkamhi et al. (2023), where in these authors search newspaper articles for terms associated with Economic and Policy Uncertainties (EPUs) and, based on the search count results, construct indexes of uncertainty. An alternative to this is to extract uncertainty from Stochastic Volatility (SV) estimates of various types of small and large-scale structural models analyzed in the macroeconomics and finance literature. As for our metric of uncertainty, motivated by the recent work on the nexus between growth and growth uncertainty by Balcilar and Ozdemir (2020), Balcilar et al. (2022), and Cepni et al. (2024), we use the second route, because the first approach is not applicable in the context of our analysis due to unavailability of the uncertainty-related indicators at the weekly frequency, with the EPUs being only available in an unbalanced manner at the monthly-level. Hence, our measure of state-level uncertainty is derived from SV estimates of the corresponding time-series of each of the 50 ECIs.[2] Although we could have also relied upon Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, which have a deterministic volatility-generating mechanism, we prefer the SV approach because it does not impose restrictions on conditional moments (as in GARCH models). In addition, SV models have also been shown in the earlier literature to produce a better in-sample fit (as well as superior out-of-sample forecasts) of volatility and, hence, uncertainty (as discussed in detail by Balcilar and Ozdemir (2020)). More specifically, we assume that the ECI of each state follows an *AR(2)* process with stochastic volatility: $ECI_t = b_1 ECI_{t-1} + b_2 ECI_{t-2} + \sqrt{exph_t}\varepsilon_t, \varepsilon_t \sim i.i.d.N(0,Q), h_t = h_{t-1} + \sigma_h v_t, v_t \sim i.i.d.N(0,1)$, where h_t is the volatility which follows a random walk process.

To produce the metrics of climate risks, we collect daily weather data from the Bloomberg terminal, as compiled by the National Climatic Data Center (NCDC), for the 50 states. The weather data captures meteorological phenomena along several dimensions, including temperature, precipitation, number of heating degree days (HDD), number of cooling degree days (CDD), and wind speed as described below:

• Temperature ($temp_t$): The average temperature (usually of the high and low) that was observed between 7 am and 7 pm local time, expressed in Fahrenheit.

[2] We assume that the ECI of each state follows an *AR(2)* process with stochastic volatility: $y_t = b_1 y_{t-1} + b_2 y_{t-2} + \sqrt{exph_t}\varepsilon_t, \varepsilon_t \sim i.i.d.N(0,Q), h_t = h_{t-1} + \sigma_h v_t, v_t \sim i.i.d.N(0,1)$, where y_t is the ECI for each state at time period t, and h_t is the volatility which follows a random walk process.

• HDD (H_t): The number of degrees that the average temperature of a day is below 65 degrees Fahrenheit. It is used to calculate the heating requirements of a building.

• CDD (C_t): The number of degrees the average temperature of a day is above 65 degrees Fahrenheit, aiding in estimating the cooling needs of a building.

• Precipitation ($prec_t$): The amount of rain, snow, sleet, or hail that falls in a specific location.

• Wind speed ($wind_t$): The average speed of the wind, not accounting for gusts, represented in knots.

As in Choi et al., (2020), we decompose the weather-related variables into three components that account for seasonal, predictable, and abnormal patterns. In particular, for each day, *t*, we compute the daily weather measure (W_t) for each of the states as a time-series, based on: $W_t = W_t^M + W_t^D + W_t^A$, where W_t = {$temperature_t$ ($temp_t$), HDD_t, CDD_t, $precipitation_t$ ($precip_t$), $wind\ speed_t$ ($wind_t$)}, and the term W_t^M denotes the mean of W_t for a specific-state spanning the 120 months prior to *t*. Moreover, the variable W_t^D denotes the difference of the mean of the deviation of the W_t from the daily average temperature for the particular state in the same calendar day over the last ten years and W_t^M. Finally, the variable W_t^A is the remainder (i.e., the abnormal deviation of weather conditions) and, hence, captures extreme departures from normal weather conditions. For this reason, we focus on this variable in our analysis. We standardize the abnormal deviations, commonly known as the standardized anomaly, to obtain the comprehensive measure of climate risks (CR), as given by: $CR_t = [std(temp_t^A) + std(precip_t^A) + std(CDD_t^A) - std(HDD_t^A) + std(wind_t^A)]/5$.[3] To match the weekly frequency of the ECI and its SV, we compute a corresponding weekly version of the CR by taking the daily averages over a week.

Based on data availability at the time of writing this paper, our sample period covers the 18th (3rd week of) April, 1987 to the 25th (4th week of) March, 2023.

3. Methodology and Results

3.1. Econometric Models

The linear panel LP model of Jordà (2005) for computing IRFs of ECIs due to an innovation (Shock) to uncertainty is specified as follows:

$$ECI_{i,t+s} = \alpha_{i,s} + \beta_s UShock_{i,t} + \gamma_{t,s} + \epsilon_{i,t+s}, \text{ for } s = 0,1,2, \ldots H \tag{1}$$

[3] Note that in CR_t, the standardized HDD_t^A enters with negative sign. HDD is a measure used to estimate the demand for energy needed to heat a building. Hence, high HDD indicates that more energy is needed to heat buildings due to lower temperatures, which implies less risk of global warming.

where $ECI_{i,t+s}$ is the ECI of the US state i in week $t + s$, with s being the forecast horizon.[4] The coefficient β_s captures the response of $ECI_{i,t+s}$ in week $t + s$ to $UShock_{i,t}$ in week t, and the shock is given by the innovation of the SV associated with the ECI in the US state i in week t.[5] We also account for unobserved heterogeneity across the states and time periods by including cross-section- and time-fixed-effects in the panel specification, indicated $\alpha_{i,s}$ and $\gamma_{t,s}$, respectively. The IRFs from the LP method are computed as a series of β_s estimated separately for each horizon.

Following the approach of Gorodnichenko and Auerbach (2013) and Jordà et al., (2020), we also use a regime-dependent model that includes a smooth transition function, to obtain the nonlinear IRFs on the ECI due to the uncertainty (SV) shock (*UShock*) contingent on low- and high-level of *CR*. We specify the regime-dependent model as follows:

$$ECI_{i,t+s} = \left(1 - F\left(z_{i,t}\right)\right)\left[\alpha_{i,s}^{High} + \beta_s^{High} UShock_{i,t} + \gamma_{t,s}^{High}\right] + F\left(z_{i,t}\right)\left[\alpha_{i,s}^{Low} + \beta_s^{Low} UShock_{i,t} + \gamma_{t,s}^{Low}\right] + \epsilon_{i,t+s}, \qquad \text{for } s = 0,1,2, \dots H \tag{2}$$

$$F\left(z_{i,t}\right) = \exp(-\gamma z_{i,t})/1 + \exp(-\gamma z_{i,t})\,, \gamma > 0, \tag{3}$$

where $z_{i,t}$ is a switching variable capturing the *CR* of the US states, which is normalized to have a mean of zero and variance of unity. $F\left(z_{i,t}\right)$ is the smooth transition function that has a bound between 0 and 1, with values close to 1 (0) representing the low (high)-CR regime. Superscripts *High* and *Low* denote the regimes of high- and low-*CR*, respectively.

3.2. *Empirical Findings*

In Figure 1, we report the IRF of the ECI due to a one-unit increase in the *UShock* capturing the innovation to the SV over 52 weeks, along with the 95% confidence bands calculated based on panel-corrected standard errors.

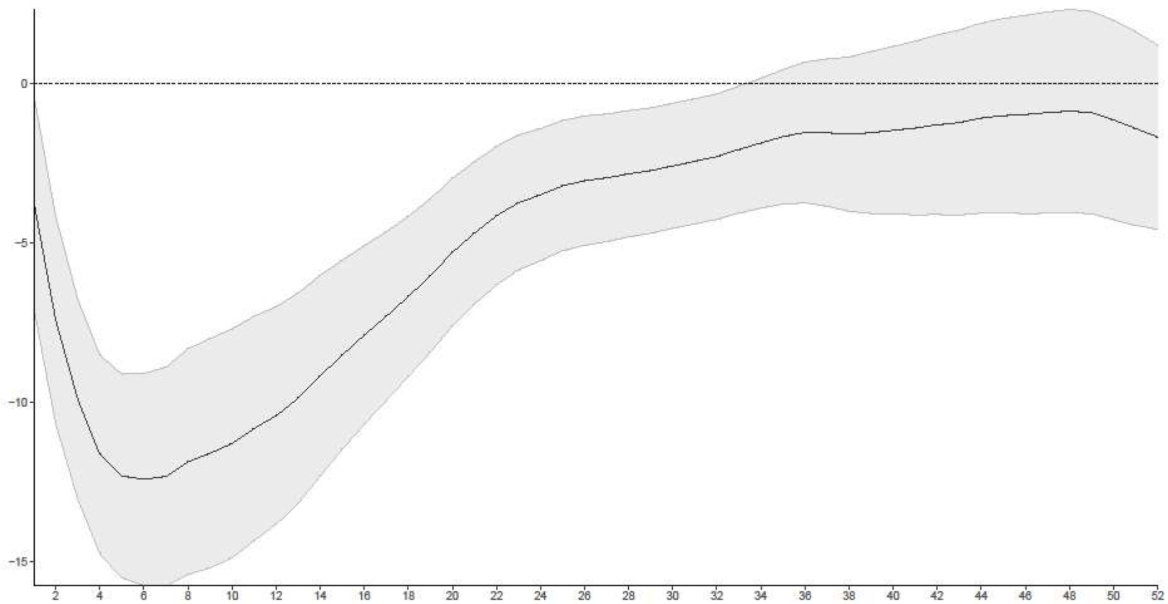
As can be seen from Figure 1, following a positive (unfavourable) uncertainty shock, the ECI of the US states deteriorate immediately upon impact. The uncertainty shock tends to exert a large negative effect on the ECI in the short term, with the impact peaking within 6 weeks to more than twelve units. Furthermore, we find that the negative effect of the shock involving the SV of the ECI stays significantly until the 34th-week-ahead horizon, i.e., more than eight quarters. More importantly, our findings are in line with the theoretical predictions of the

[4] The maximum length of forecast horizon is set to 52 in this study, corresponding to a year.

[5] $Shock_{i,t}$ is obtained from the residuals of and *AR(1)* fixed-effects panel data model of the US states which involves regressing of the SV of the ECI of each state on its own first lag.

adverse impact uncertainty is expected to have on the economy emanating from both aggregate demand and aggregate supply channels. We also confirm the lower-frequency state-level negative effects of uncertainty detected by the existing empirical literature, which we now show to extend to weekly economic conditions, encapsulating six dimensions of the US states.

Figure 1: The IRF of US State-Level Economic Conditions Indexes (ECIs) following a Positive Uncertainty Shock (*UShock*)

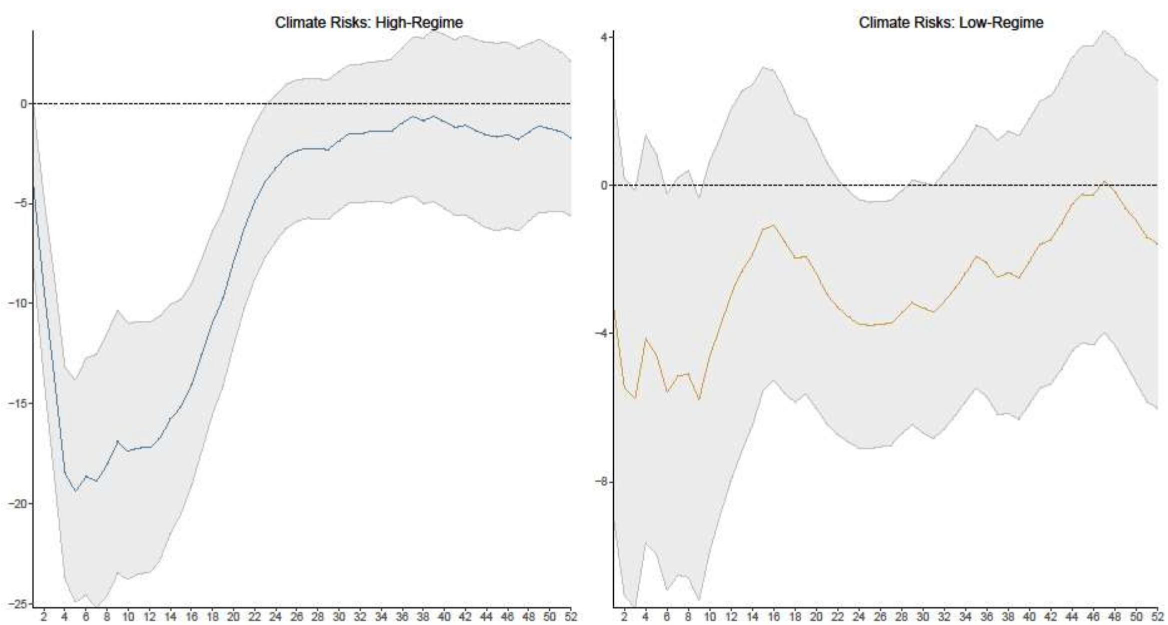


Next, in Figure 2, we turn to test the main hypothesis of our paper, which is that the negative effect observed in Figure 1 for the state-level ECIs, are likely to be stronger in regimes characterized by relatively higher risks associated with extreme weather events. For this, we rely on the climate risks-based-regime-specific IRFs of the ECI following a one-unit increase in *UShock*.

As observed from the left panel of Figure 2, the maximum negative impact of a positive uncertainty shock on the state-level ECIs is relatively stronger, i.e., more severe, when the US states are in the high-regime of climate risks, to the extent that the same effect, though negative, is not statistically significant in general in the low-climate risks-regime. Specifically speaking, when climate risks are aggravated, following a one-unit uncertainty shock the state ECIs are reduced to more than nineteen units at the 5th-week-ahead horizon, with the effect staying significant till 24-week-ahead. In contrast, when the states are facing lower climate risks, the maximum impact of the *UShock* is not only less prominent in terms of magnitude, but more importantly, in terms of statistical significance given the 95% confidence bands. Only intermittent significant negative effects to the order of five units at the 3^{rd}-, 6^{th}-, and 9^{th}-week-ahead horizons, and three units over the 22^{nd}- to 28^{th}-week-ahead are observed following the positive one-unit uncertainty shock.

When we compare Figures 1 and 2, it is evident that the regime-independent results reported in the former figure are basically driven by the effect of uncertainty on the state ECIs under the high regime associated with climate risks, and only to a limited degree by the impact under the lower-extreme weather-related-regime, in terms of the persistence of the effect associated with the length of the weeks-ahead following the shock. Though the initial impact of the nonlinear model under the high climate risk regime mimics that of the linear model, the maximum effect is much stronger in the regime-dependent case, since the overall linear effect on the state-level ECIs is muted by the lower-regime of climate risks. These observations, confirm our hypothesis that higher climate risks can deepen the recessionary impact of uncertainty shocks.

Figure 2: The Climate Risks-Based-Regime-Specific IRFs of the US State-Level Economic Conditions Indexes (ECIs) following a Positive Uncertainty Shock (*UShock*)



When we dive deeper into why this might be the case, especially in high climate risk regimes, several aggregate supply- and aggregate demand-channels come into play. Firstly, high climate risks, such as increased frequency of extreme weather events, can lead to significant economic disruptions, which can range from range from damages to infrastructure and property, adversely impacting supply chains, to declines in productivity due to workforce dislocation or health impacts. Such tangible impacts of climate risks can enhance the negative effects of economic uncertainty. In addition, the uncertainty associated with climate risks can also lead to higher insurance costs, increased precautionary savings, and diverted resources from productive investment towards disaster preparedness and recovery efforts. These factors can further strain the economic conditions of states, particularly those that are more susceptible to extreme weather events. In essence, in states with high climate risks, the usual channels through which uncertainty affects the economy—such as investment and consumption decisions—are compounded by the additional risks and costs associated with climate change. This results in a more pronounced economic downturn in response to uncertainty shocks, as reflected by a relatively greater drop in the ECIs for the states in the high-regime associated with climate change-related risks.

4. Conclusion

In this paper, we analyse the effect of uncertainty on a broad measure of economic conditions of the 50 US states, over the weekly period of the 3rd week of April 1987 to the 4th week of March 2023, conditional on the high- and low-regimes of corresponding state-level extreme weather risks. Our results, based on linear and nonlinear panel data models of local projections, show that, while uncertainty, as captured by conditional stochastic volatility of the economic conditions indexes (ECIs), negatively impact the ECIs in a statistically significant fashion, these effects are immensely magnified when climate risks correspond to the upper-regime. This is because, stronger abnormal weather events, corresponding to its high regime, lead to enhancement of the adverse effects of the demand- and supply-side channels through which uncertainty tends to impact the ECIs.

Our findings imply that, while policies aiming at reducing uncertainty will improve economic conditions, the size of such positive effects would be contingent on the level of the underlying climate risks. In other words, policymakers would need to pursue complementary policies, in the sense that such measures would need to ensure simultaneous reduction of uncertainty and climate risks, to produce the desired economic effects. In addition, stronger expansionary policy responses are required when climate risks are relatively higher across the states.

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