



Working Paper Series

Extreme Weather and the Macroeconomy

WP 21-14

Hee Soo Kim
Indiana University

Christian Matthes
Indiana University

Toan Phan
Federal Reserve Bank of Richmond

This paper can be downloaded without charge
from: <http://www.richmondfed.org/publications/>



Richmond • Baltimore • Charlotte

Extreme Weather and the Macroeconomy

Hee Soo Kim*, Christian Matthes* & Toan Phan**

August 11, 2021

Abstract

We investigate the macroeconomic effects of changes in extreme weather in the United States over the past sixty years by incorporating the Actuaries Climate Index (ACI) into a smooth transition vector autoregressive analysis of the United States economy. The ACI tracks changes in the distribution of extreme temperatures, heavy rainfall, drought, high wind, and sea level. While the effects of extreme weather events are negligible at the beginning of the sample, they become more significant later: An increase in the index now persistently reduces the *growth rate* of industrial production while raising the unemployment rate and inflation.

Keywords: extreme weather, STVAR, growth, inflation

JEL codes: E23, Q54

*Indiana University; **The Federal Reserve Bank of Richmond. The views expressed here are those of the authors and should not be interpreted as those of the Federal Reserve Bank of Richmond or the Federal Reserve System. Contacts: hk74@iu.edu, matthesc@iu.edu, and toanvphan@gmail.com. We would like to thank Ariel Burstein, Larry Christiano, Miles Parker, and James Stock as well as seminar participants at the Richmond Fed and the CEBRA 2021 conference for helpful discussions and comments.

1 Introduction

How do environmental shocks, in particular extreme weather shocks, affect the macroeconomy? Exploiting a novel meteorological time series for extreme weather - the Actuaries Climate Index (or ACI) - we investigate this question via a smooth transition vector autoregressive analysis (VAR) of United States national macroeconomic variables over the past six decades. We find that shocks to the ACI have few discernible effects at the beginning of the sample, when the ACI was relatively low. However, the effects are statistically and economically significant at the end of the sample when the ACI is relatively high: an increase in the extreme weather index causes a damage to the *growth rate* of national industrial production (IP), an increase in the national unemployment rate, and an increase in the consumer price index (CPI) inflation. The effects are persistent up to about 20 months.

The investigation of the economic effects of weather and climate-related shocks has been the focus of a large and growing body of research (e.g., see recent literature reviews by [Dell et al. 2014](#); [Hsiang 2016](#); [Giglio et al. 2020](#)). Estimating the macroeconomic effects of extreme weather shocks and natural disasters remains a critical open question, as the literature has found mixed results, with some papers suggesting limited or no effects on growth and others documenting very persistent damages (e.g., [Noy 2009](#); [Strobl 2011](#); [Cavallo et al. 2013](#); [Felbermayr and Gröschl 2014](#); [Hsiang and Jina 2014](#); [Bakkensen and Mendelsohn 2016](#); [Bakkensen and Barrage 2019](#); [Tran and Wilson 2020](#)). Recent papers have argued that the quality of the measure of extreme weather shocks as an independent variable has been an issue. For instance, many international studies have used the self-reported disaster counts and losses from the Emergency Events Database (EM-DAT) and many studies for the United States have used similar datasets that are derived from official death or damage statistics.¹ Official or self-reported statistics of direct disaster damages (in dollars or deaths) may underestimate the full extent of actual damages² and their

¹Examples are the Billion-Dollar Weather and Climate Disasters data assembled by the National Oceanic and Atmospheric Administration (NOAA) or the Spatial Hazard Events and Losses Database for the United States (SHELDUS) assembled by Arizona State University.

²For example, [Kishore et al. \(2018\)](#) estimated that the number of excess deaths related to

quality and completeness may endogenously depend on the local economic or political conditions (e.g., [Kahn 2005](#); [Hsiang and Narita 2012](#); [Hsiang and Jina 2014](#)). For these reasons, we employ a novel index for extreme weather, constructed using physical and meteorological observations of temperatures, rainfall, drought, wind speed, and sea level, which are arguably less subject to the aforementioned endogeneity or quality concerns.

To analyze our data, we employ a vector autoregressive (VAR) analysis, which is a workhorse model in empirical macroeconomics ([Sims 1980](#)). Since we are interested in how the effects of extreme weather on the United States economy have changed over time, we have to adjust our empirical strategy to take into account parameter variation. We could do so in various ways. For example, we could simply split the sample. Since our ACI data is made up of a reference period and the subsequent data, we have a natural data at which to split the sample. Nonetheless, we might not be efficiently using all available data by simply splitting the sample. As our benchmark, we thus use a smooth transition VAR (STVAR) to exploit all available data in our estimation ([Auerbach and Gorodnichenko 2012](#)) and keep the sample split as a robustness check. In such models, the VAR parameters are determined as a convex combination of two sets of parameters, with weights being a function of a predetermined observable. We study various choices of this predetermined variable, from a simple time transition to lagged averages of our ACI index, and lagged averages of CO2 concentration in the atmosphere.

Our findings suggest that increases in extreme weather can cause persistent damages to economic growth and affect price stability in the United States. These findings have important implications. First, climate change is predicted to increase the frequency or intensity of extreme weather such as cyclones, flooding, droughts and heat waves ([Emanuel et al. 2008](#); [Mendelsohn et al. 2012](#); [Stott 2016](#)). Our estimates can be useful for the calculation of the social cost of carbon and the calibration of the climate damage function that underlies the work horse integrated assessment models (e.g., [Nordhaus 1993](#); [Golosov et al. 2014](#); [Hassler and Krusell 2018](#)).

Second, while the previous literature has documented substantial negative effects

Hurricane Maria in Puerto Rico is more than 70 times the official estimate.

of weather and climate-related shocks on economic growth in developing countries (e.g., see [Dell et al. 2012](#); [Von Peter et al. 2012](#); [Bakkensen and Barrage 2019](#)), it has been more challenging to provide systematic evidence that weather shocks can affect the aggregate macroeconomy in developed economies like the United States, where some prominent scholars have conjectured that the effects are likely limited (e.g., [Schelling 1992](#); [Mendelsohn 2010](#); [Nordhaus 2014](#)). Much of the existing evidence for the United States has focused on subsections of the economy that are naturally exposed to outdoor weather conditions.³ We contribute to this literature by providing evidence that weather shocks do affect the United States economy, even at the aggregate national level. Furthermore, in the macroeconomic literature, natural disaster shocks are typically thought to have short-lived effects in the United States. Our findings suggest the contrary. Interestingly, our estimate of the persistent effects of a shock to the extreme weather *index* on IP growth in the United States echoes recent estimates of the effects of extreme weather *events* on economic growth in a panel of countries around the world (e.g., [Hsiang and Jina 2014](#); [Bakkensen and Barrage 2019](#)), even though as expected, our documented effects are smaller and less persistent.^{4,5}

Third, the fact that our time-varying estimates of the extreme weather effects are stronger in recent years also suggests that there may be limited adaptation to extreme weather shocks. This echoes existing findings in a growing empirical literature on

³E.g., see [Roberts and Schlenker \(2013\)](#), [Burke and Emerick \(2016\)](#) and references therein for evidence of weather effects on United States agriculture. Some exceptions include [Deryugina and Hsiang \(2017\)](#) and [Colacito et al. \(2019\)](#), which document the negative effects of temperature shocks on county-level income or state-level GDP growth in the United States. Also see [Hsiang et al. \(2017\)](#) for a broad survey of empirical estimates for the United States agriculture, labor supply, productivity, or health, and [Hong et al. \(2020\)](#) for a survey of recent estimates of the effects on asset prices in the United States.

⁴For instance, while an extreme weather shock reduces IP growth in the United States for 20 months in our recent sample, [Hsiang and Jina \(2014\)](#) find that a cyclone shock reduces GDP per capita growth in a panel of countries across the world for 20 years.

⁵A limitation of our project is that currently, we do not have evidence as to which underlying mechanism is likely to be at play. Potential mechanisms that explain such persistent effects of extreme weather shocks include financial frictions that amplify and propagate the direct damage of a shock ([Phan and Schwartzman 2021](#)), psychological factors that permanently alter the preferences of affected individuals ([Cameron and Shah 2015](#)), or divestment in durable human or physical capital in disaster-prone areas ([Alvarez and Rossi-Hansberg 2021](#)).

climate adaptation (e.g., [Hornbeck 2012](#); [Burke and Emerick 2016](#); [Bakkensen and Mendelsohn 2016](#); [Barrage and Furst 2019](#)).⁶

Finally, our findings on the effects of extreme weather shocks on inflation in the recent sample also have relevant policy implications. While the previous literature has found effects of weather shocks on inflation mainly in developing economies ([Parker 2018](#)), the concern that climate-related shocks may affect price stability has been revived in recent policy discussions among advanced countries' central banks.⁷ Our systematic evidence on the effects of extreme weather on noncore (mainly energy and food) prices also corroborates recent anecdotes of how extreme weather shocks can lead to dramatic increases in energy prices.⁸

In a related paper, [Ludvigson et al. \(2020\)](#) analyze economic disaster shocks in the United States to study the effects of billion-dollar natural disasters and the recent COVID-19 pandemic. Although many of the disasters in their dataset are weather-related (e.g., hurricanes), our dataset covers substantially different events, such as changes in very low or very high temperatures that would not be classified as disasters by [Ludvigson et al. \(2020\)](#). Our paper is also related to the growing econometric analysis of climate change and its associated economic effects (see, for example, [Pretis et al. 2018](#), [Chang et al. 2020](#), [Diebold et al. 2020](#), and [Metcalf and](#)

⁶Note that [Barreca et al. \(2016\)](#) documented that the United States has adapted to reduce the effects of extreme heat on mortality via the adoption of air conditioning. However, despite the widespread adoption of air conditioning in the United States, [Cachon et al. \(2012\)](#) found that high temperatures decrease productivity and performance in the United States automobile sector, and [Graff Zivin and Neidell \(2014\)](#) found large reductions in time allocated to labor in industries that are exposed to weather conditions.

⁷For example, the European Central Bank (ECB) officially stated on July 8, 2021, their plan to incorporate climate change considerations into its monetary policy strategy. A justification is that “[c]limate change and the transition towards a more sustainable economy affect the outlook for price stability through their impact on macroeconomic indicators such as inflation, output, employment, interest rates, investment and productivity; financial stability; and the transmission of monetary policy.” The ECB president Christine Lagarde also recently stated that “Climate change can create short-term volatility in output and inflation through extreme weather events, and if left unaddressed can have long-lasting effects on growth and inflation” (25 January 2021 speech on “Climate change and central banking”). Staffs of the Bank of England also issued similar statements ([Batten et al. 2020](#)).

⁸See, for example, “His Lights Stayed on During Texas’ Storm. Now He Owes \$16,752,” the *New York Times* 20 February 2021 (<https://www.nytimes.com/2021/02/20/us/texas-storm-electric-bills.html>).

[Stock 2020](#)).

The rest of the paper is organized as follows. Section 2 describes the extreme weather index and other macroeconomic variables. Section 3 describes the econometric model, and Section 4 provides the results. Section 5 concludes.

2 Data

2.1 The Actuaries Climate Index

The ACI, developed by actuary associations in the United States and Canada as a monitoring tool ([American Academy of Actuaries, Canadian Institute of Actuaries, Casualty Actuarial Society and Society of Actuaries, 2020](#)), is an aggregate indicator of the frequency of extreme weather and the extent of sea level rise. The monthly index, available for the United States and Canada, tracks the following six components:

1. High temperatures (T_{90}), which tracks the change in the frequency of temperatures above the 90th percentile relative to the reference period (1961 to 1990).
2. Low temperatures (T_{10}), which similarly tracks the change in the frequency of temperatures below the 10th percentile.
3. Heavy precipitation (P), which tracks the maximum five-day rainfall in the month.
4. Drought (D), which tracks the maximum number of consecutive days with less than 1mm of daily precipitation.
5. High wind (W), which tracks the change in the frequency of wind power (the cube of wind speed) above the 90th percentile relative to the reference period.
6. Sea level (S), which tracks the change in the sea level (measured via tide gauges located at permanent coastal stations in the United States and Canada).

To combine the components, the monthly difference of each component relative to the reference period (1961-1990) is divided by the reference period’s standard deviation. This ratio is usually known as the standardized anomaly. For example, the standardized anomaly of P in January 2010 measures how unusual that month’s value of precipitation is compared to the reference period’s mean and standard deviation for precipitation in January. Let P_{std} denote the standardized anomaly for precipitation (and similarly for other components; the subscript reflects the fact that the anomaly is in units of the standard deviation of each component). The ACI is then defined as⁹

$$ACI = \text{mean}(T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + S_{std}).$$

As our analysis focuses on the United States, we use the ACI available for the continental United States. Figure 1 plots the ACI for the continental United States and Figure 2 plots the corresponding six components.

2.2 Macroeconomic Data

Besides the ACI, we employ a set of standard macroeconomic measures for the United States, all at the monthly frequency and available from the Federal Reserve Bank of St Louis’ Federal Reserve Economic Data (FRED): industrial production growth, consumer price index (CPI) inflation, core CPI inflation, the short-term interest rate (the effective federal funds rate)¹⁰, and the unemployment rate. One important aspect of our data choices is that we use industrial production to be able to use monthly data (gross domestic product is only available at a quarterly frequency). Using more high-frequency data is important as some weather effects can be short-lived. Industrial production does, by definition, not measure agricultural output, which is a key area where extreme weather can influence outcomes (Nordhaus, 1991).

⁹The sign of $T10$ is negative to reflect the fact that extreme cold days are less likely due to the recent warming trends in temperatures. According to the ACI documentation (<https://actuariesclimateindex.org/about/>), “An increased value of the Index due to the reduction in cold extremes is consistent with an increased risk of perils due to melting permafrost, the propagation of diseases, and the population of pests and insects that were previously less likely to survive in lower temperatures.”

¹⁰During and after the financial crisis, we use the updated Wu and Xia (2016) shadow rate.

Hence, our estimated effects on industrial production provide a lower bound on the overall real effects of extreme weather.

We provide further descriptions of our data sources in Appendix A. Note that growth and inflation are measured as year-on-year changes.

We seasonally adjust our data using the standard Census Bureau X-13 seasonal adjustment algorithm. Figure 3 plots the seasonally adjusted time series of the variables employed in our empirical analysis: ACI, IP growth, CPI and core CPI inflation, short-term interest rate, and unemployment rate. In Appendix C, we both show that our seasonal adjustment does indeed remove the seasonal patterns in the ACI index, but that our results are also robust to using non-seasonally adjusted data (for both the ACI and the macroeconomic variables we study).

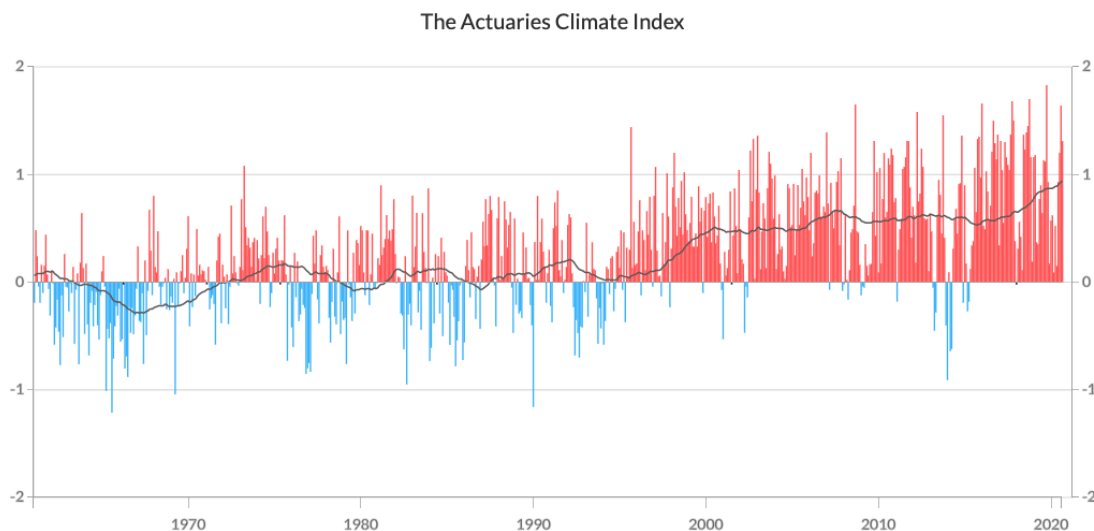


Figure 1: The ACI time series for the continental United States. The bars plot the monthly values of the index (relative to the reference period of 1961-1990), with red (blue) bars indicating values that are positive (negative). The solid line plots the five-year moving averages. Source: <https://actuariesclimateindex.org/explore/regional-graphs>

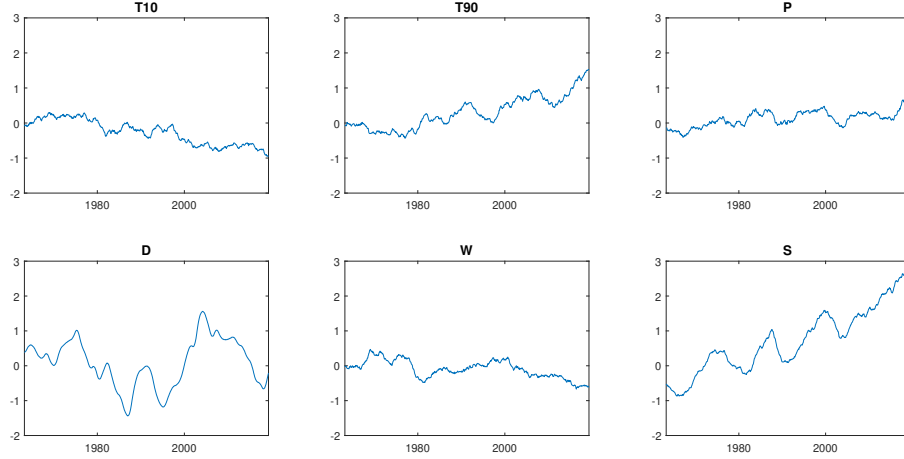


Figure 2: The six components of the ACI (low temperatures, high temperatures, heavy precipitation, drought, high wind, and sea level) for the continental United States.

3 Econometric Models

3.1 A Building Block: Linear VAR

To describe the various models we use to analyze our monthly data, it will be useful to first describe the standard linear VAR that forms the backbone of our nonlinear time series models. We stack the aforementioned observables at time t in a column vector \mathbf{y}_t . A linear VAR is then described by the following equation:

$$\mathbf{y}_t = \mathbf{m} + \sum_{\ell=1}^{\mathcal{L}} \mathbf{A}_{\ell} \mathbf{y}_{t-\ell} + \mathbf{\Sigma} \mathbf{e}_t \quad (1)$$

where $\mathbf{e}_t \sim_{iid} N(\mathbf{0}, \mathbf{I})$ is a vector of structural shocks containing as one element our shock of interest. We order ACI first in \mathbf{y}_t and, without loss of generality, assume that the first element of \mathbf{e}_t is our shock of interest.

Our key identification assumption is that economic shocks do not have contemporaneous effects on the ACI. Any unexpected changes in the economy from one

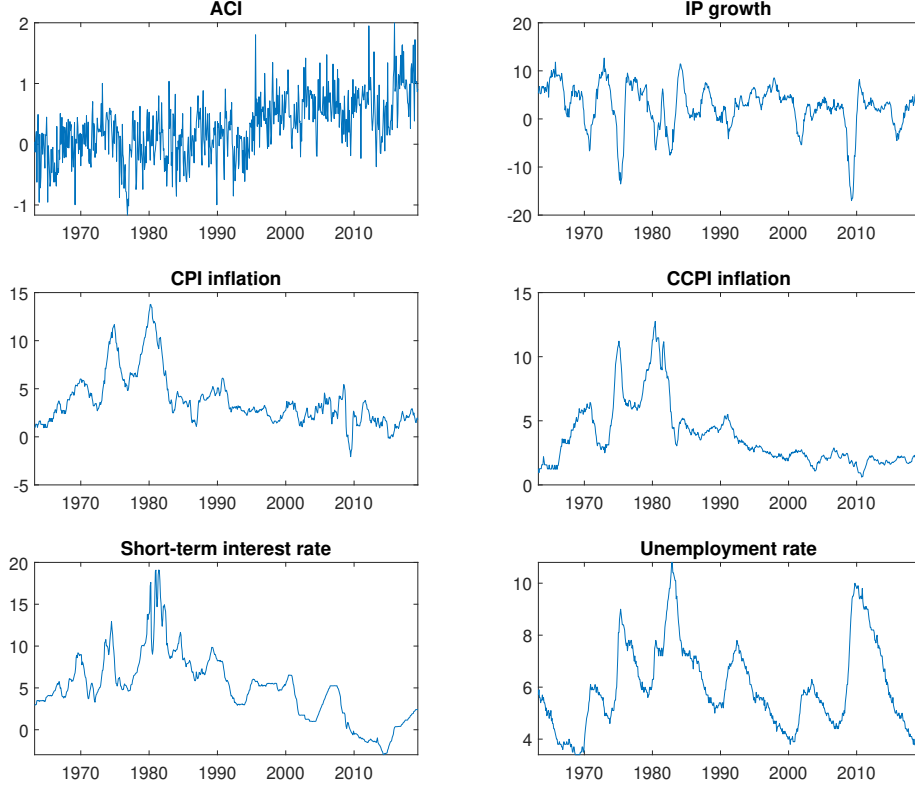


Figure 3: Monthly time series used for empirical analysis: the Actuary Climate Index (ACI), year-on-year Industrial Production (IP) growth, year-on-year Consumer Price Index (CPI) inflation, Core CPI inflation, short-term interest rate, and unemployment rate.

month to the next are thus assumed to have no influence on the occurrence of extreme weather events in that next month. Given that economic activities are unlikely to be able to immediately affect the weather, we believe that this is a reasonable assumption. Note that this does *not* mean that long run trends of economic variables cannot influence ACI outcomes.

Formally, define the one-step ahead forecast error implied by equation (1) as $\mathbf{u}_t := \mathbf{y}_t - E_{t-1}\mathbf{y}_t = \Sigma\mathbf{e}_t$. We assume that all variation in the ACI coming from

\mathbf{u}_t is due to the ACI shock we want to identify. Mathematically, our identification assumption is encoded in restrictions on the matrix Σ as follows: the first element of \mathbf{u}_t is equal to a constant Σ_{11} times the first element of \mathbf{e}_t . This restriction implies that all elements in the first row of Σ except for the very first element Σ_{11} are equal to zero. We normalize the first element to be positive (this amounts to defining a positive shock as one that raises ACI, everything else equal). To achieve exact identification of all elements of Σ , we additionally assume that Σ and its counterparts in our nonlinear models introduced below are lower triangular. Note that this does not restrict the identification of the effects of our ACI shock, since the identification restrictions for this shock are the same whether or not we impose additional zero restrictions on Σ that pin down the effects of the other elements of \mathbf{e}_t . What these additional zero restrictions give us is a more well behaved likelihood function for the non-ACI shock elements of Σ .

Speaking of the likelihood function, we use the Gaussian assumption on \mathbf{e}_t to build the likelihood function of the data, which we then combine with a prior in Bayesian inference.

3.2 Main Model: Smooth Transition VAR

To analyze possible parameter and volatility changes, we use smooth transition VARs (STVARs) as in [Auerbach and Gorodnichenko \(2012\)](#) (see also [Granger and Terasvirta 1993](#) for related models). While there are alternative models for time-varying parameters and stochastic volatility in VARs (see, for example, [Sims and Zha 2006](#); [Cogley and Sargent 2002](#), or [Primiceri 2005](#)), we choose this form because it makes the way parameters change transparent, and it fits nicely with our economic question: Are the effects of extreme weather events different now than they were fifty or sixty years ago? Other models of time-varying parameters might pick up higher frequency changes in the relationships between our variables, such as changes in the monetary transmission mechanism.

The idea behind STVARs is straightforward: There are two possible extreme realizations of the parameter values $(\{\mathbf{m}_j, \{\mathbf{A}_{\ell,j}\}_{\ell=1}^{\mathcal{L}}, \Sigma_j\}_{j=1,2})$, and at each point

in time the dynamics are governed by a convex combination of these two. The weights for the convex combination are determined by a variable \tilde{z}_{t-1} , which is either exogenous or can only be a function of observable variables up to and including time $t - 1$:

$$\mathbf{y}_t = (1 - \tilde{z}_{t-1})(\mathbf{m}_1 + \sum_{\ell=1}^{\mathcal{L}} \mathbf{A}_{\ell,1} \mathbf{y}_{t-\ell} + \mathbf{\Sigma}_1 \mathbf{e}_t) + \tilde{z}_{t-1}(\mathbf{m}_2 + \sum_{\ell=1}^{\mathcal{L}} \mathbf{A}_{\ell,2} \mathbf{y}_{t-\ell} + \mathbf{\Sigma}_2 \mathbf{e}_t), \quad (2)$$

where, again, $\mathbf{e}_t \sim_{iid} N(\mathbf{0}, \mathbf{I})$. We will study various choices for \tilde{z}_{t-1} . As our benchmark, we use a simple time-dependent transition:

$$\tilde{z}_t := \frac{t+1}{T}, \quad \forall 0 \leq t \leq T. \quad (3)$$

As in the linear VAR described in the previous section, our identifying assumption is that Σ_1 and Σ_2 are lower triangular.

Note that here our purpose this time transition is an efficient way to use all available data to inform us about time variation in parameters rather than splitting the sample. The alternatives for \tilde{z}_t that we consider are rescaled lagged averages of ACI and CO2 concentration in the atmosphere. Both have a clear upward trend. Given this common shape for our transition variables, we will call parameters with a subscript of 1 beginning-of-sample parameters and those with a subscript of 2 end-of-sample parameters. Note that this is different from the use of smooth transition VARs to study differences across recessions and expansions, as in [Auerbach and Gorodnichenko \(2012\)](#), for example.

The priors we use are described in detail in [Appendix B](#). Broadly speaking, we use standard Minnesota-type priors ([Litterman, 1986](#)) for $\{\mathbf{A}_{\ell,j}\}_{\ell=1}^{\mathcal{L}}$. As is common, the setting of a Minnesota-type prior requires a training sample. We use an empirical Bayes approach here and use our entire sample as the training sample. The prior for the nonzero elements of $\mathbf{\Sigma}$ is comprised of independent Gaussian priors for each element centered at the relevant entries of the Cholesky decomposition of the OLS-based point estimate of $\mathbf{\Sigma}\mathbf{\Sigma}'$ from the training sample. These priors are loose (standard deviation of 0.25). Similarly, the Gaussian priors for the intercept

are informed by the training sample, but with large standard deviations. *In our smooth transition models, the priors for beginning-of-sample parameters and the corresponding end-of-sample parameters are the same, so all differences that emerge in our results are driven by the likelihood function.* We approximate the posterior distribution using a sequential Monte Carlo (SMC) algorithm that has been shown to efficiently explore the parameter space in nonlinear multivariate time series models (Bognanni and Herbst, 2018).¹¹ We relegate the details to Appendix B.

4 Results

The results from our STVARs are as follows. Figure 4 plots the impulse response functions (IRFs) of macro variables to a one-time one-standard-deviation shock to the ACI.¹² The top blue panels show the responses at the beginning of the sample (i.e., where the time transition variable is $\tilde{z}_t = 0$), while the bottom red ones show those at the end (i.e., where $\tilde{z}_t = 1$). The shaded areas represent 68% posterior bands.

Let us first look at the responses of year-on-year IP growth, as reported in the second column of the figure. The ACI shock has no statistically significant¹³ effect at the beginning of the sample. However, the shock has a statistically significant persistent effect on IP growth at the end of the sample. Upon impact, the ACI shock reduces IP growth by 0.12 percentage points. Furthermore, the effect is persistent and can be felt even after nearly 20 months (after which there seems to be some bounce back, as indicated by the fact that the coefficient estimate for IP growth goes slightly above zero; however, the coefficient estimate is no longer statistically significant then). This persistent damage of weather shocks echoes the findings in previous studies, including Dell et al. (2012), Colacito et al. (2019), and Hsiang and Jina (2014), which find persistent damages on output growth from temperature

¹¹See also Waggoner et al. (2016) for a similar algorithm.

¹²To compute these impulse responses, we hold \tilde{z}_{t-1} fixed at either 0 or 1. This type of assumption is common when computing impulse responses in time-varying parameter models (Primiceri, 2005).

¹³We use "statistical significance" in this paper to indicate whether the posterior bands include 0 or not.

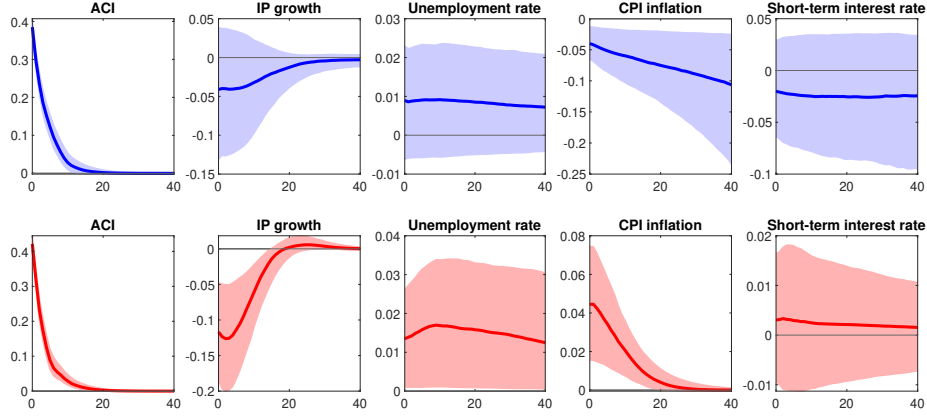


Figure 4: Main results: Impulse responses of macro variables to a one-standard-deviation shock to the ACI. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands.

shocks and tropical cyclone shocks via panel regression analyses. As in these papers, a limitation is that we do not know what the key underlying mechanisms driving such persistent damages could be.

To assess the economic significance of our estimates, we use our VAR model to compute variance decompositions, holding the VAR parameter fixed at either the beginning or the end of the sample (just as we did with IRFs). Generally, the numbers are economically significant, in particular at the end of the sample. The posterior median for the effects of the ACI shock on macroeconomic variables is between 1 and 2 percent, both on impact ($h=0$) and one year out ($h=12$). The 84th posterior percentile highlights that this shock can be a relevant contributor to economic fluctuations, with values between 3 percent and 5 percent across variables and horizons. For the sake of comparison, the well-known [Smets and Wouters \(2007\)](#) DSGE model attributes less than 10 percent of fluctuations in GDP and inflation at its point estimate to monetary policy shocks at similar horizons.

The persistent damage on IP growth would imply an even more persistent damage on the level of IP. To investigate this, we re-estimate our STVAR, but substitute IP growth with the natural log of the IP level. Figure 5 plots the corresponding impulse

Beginning of Sample										
	ACI		IP growth		Unemployment rate		CPI inflation		interest rate	
	h=0	h=12	h=0	h=12	h=0	h=12	h=0	h=12	h=0	h=12
16th	100.00%	99.97%	0.03%	0.03%	0.03%	0.03%	0.22%	0.21%	0.02%	0.01%
50th	100.00%	99.99%	0.29%	0.30%	0.37%	0.39%	1.56%	1.52%	0.15%	0.15%
84th	100.00%	99.99%	1.14%	1.16%	1.64%	1.66%	3.99%	3.96%	0.66%	0.66%
End of sample										
	ACI		IP growth		Unemployment rate		CPI inflation		interest rate	
	h=0	h=12	h=0	h=12	h=0	h=12	h=0	h=12	h=0	h=12
16th	100.00%	100.00%	0.37%	0.37%	0.11%	0.10%	0.15%	0.16%	0.11%	0.11%
50th	100.00%	100.00%	1.81%	1.79%	0.98%	0.97%	1.09%	1.12%	1.16%	1.15%
84th	100.00%	100.00%	4.79%	4.76%	3.35%	3.31%	3.21%	3.23%	5.00%	4.92%

Table 1: Variance decomposition (using 1000 draws)

response functions from this exercise. As shown in the bottom IP panel, which plots the response of the log of IP at the end of our sample, the ACI shock leads to a very persistent decline – the IP level does not recover to its pre-shock trend even after 40 months.¹⁴

Our finding also suggests that there is *nonlinearity* in the effects of the ACI shock on IP growth. Recall from Figure 3 that the average ACI level at the end of the sample is higher than that at the beginning. Figure 4 suggests that the increase in the ACI from a higher level has a stronger damage on growth. This nonlinear finding is also suggestive that there has been limited adaptation to extreme weather in the years of our sample. This is because if there had been sufficient adaptation, then we would have expected to see a weaker effect of the ACI shock on IP growth at the end of the sample. This finding also echoes existing papers in the climate adaptation literature, which so far have found mixed evidence for adaptation, including in the United States (e.g., [Hornbeck 2012](#); [Burke and Emerick 2016](#); [Mendelsohn et al. 2012](#);

¹⁴We also estimated a VAR with month/month IP growth rates and then cumulated up the IP growth responses - the results were very similar.

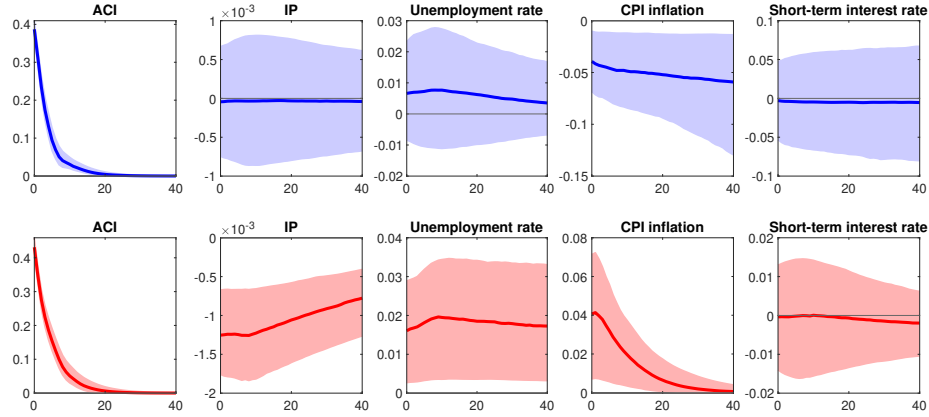


Figure 5: Log of IP level instead of IP growth. Impulse responses of macro variables to a one-standard-deviation shock to the ACI. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands.

[Bakkensen and Mendelsohn 2016](#); [Barreca et al. 2016](#)).

Returning to our benchmark results in Figure 4, the effect on the unemployment rate is similar to that on IP growth, although with less statistical significance. The ACI shock has no statistically significant effect at the beginning of the sample. However, at the end of the sample, the shock increases the unemployment rate by about 0.02 percentage point. The effect is persistent for as long as 40 months, though with less statistical significance.

Turning toward nominal variables in Figure 4, the ACI shock appears to have no statistically significant effect on the short-term interest rate. This is intuitive because we do not expect monetary policy to react directly to movements in the ACI. However, the shock appears to have a negative effect on inflation at the beginning of the sample, but have a positive effect at the end.

To understand the effects on CPI better, we conduct another analysis where we include not only the CPI inflation but also core CPI (CCPI) inflation, which excludes inflation in energy and food prices. The impulse responses in the CCPI panels of Figure 6 show core inflation does not appear to be affected by the ACI shock. This

finding is consistent with our prior intuition that if the ACI shock is to have an effect on inflation, then the effect is likely to be driven by the responses in energy and food prices.

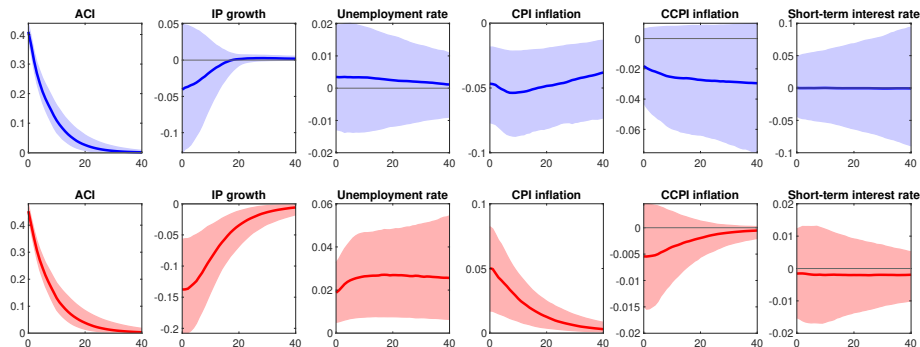


Figure 6: CPI and Core CPI: Impulse responses of inflation, core inflation, and other macro variables to a one-standard-deviation shock to the ACI. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands.

4.1 Alternative Transition Variables

In this section, we study three alternative choices for \tilde{z}_t : (i) a sample split where $\tilde{z}_t = 0$ in the period the ACI uses as a benchmark (which ends in 1990) to standardize its components and $\tilde{z}_t = 1$ afterward, (ii) five-year lagged moving averages of the ACI index itself, and (iii) five-year lagged moving averages of CO2 concentration¹⁵ in the atmosphere. The variables for choices (ii) and (iii) are rescaled to be between 0 and 1. Figure 7 shows that even when we completely disregard any information from the benchmarking period of the ACI (which ends in 1990), we still get very similar results. Posterior bands for the response of inflation now contain 0 (albeit barely), but as we discussed before, these movements are driven noncore components

¹⁵Data source for the concentration of CO2 in the air is available from NOAA(National Oceanic and Atmospheric Administration)-ESRL(Earth System Research Laboratories) Global Monitoring (<https://gml.noaa.gov/ccgg/trends/data.html>). We use CO2 records measured at Mauna Loa, Hawaii Laboratory.

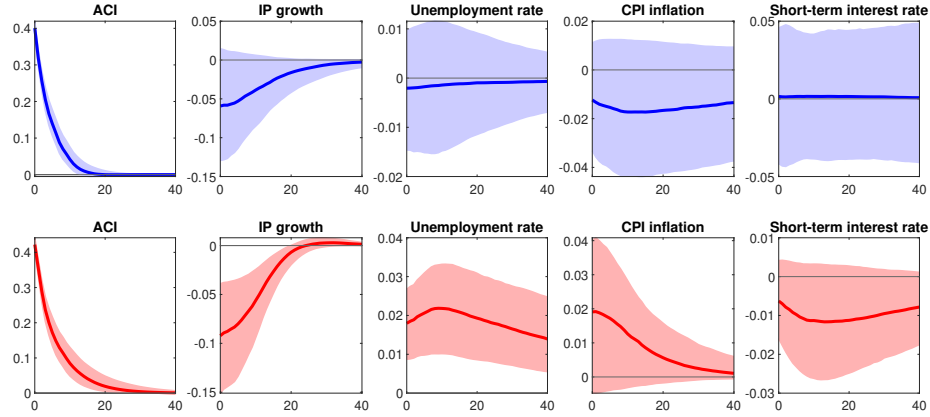


Figure 7: Results when we split the sample (choice (i)).

of inflation anyway. A question a reader might have is whether we throw away useful information about the time variation in the responses to weather events by not using more detailed information about weather or climate changes in our transition variable. Figures 8 and 9 show that this is not the case. Figure 8 uses lagged moving averages of the ACI index itself as a transition variable and again finds very similar results. The increase in unemployment is less pronounced in this specification, but given all our other specifications, that is not a robust finding.

Finally, a worry with choice (ii) might be that low frequency movements in the ACI are caused by other variables that could then be better choices for our transition variable. One such candidate is the concentration of CO₂ in the atmosphere, given the well-established scientific link between CO₂ concentration and temperature changes. Figure 9 shows that our findings are confirmed in this case as well.

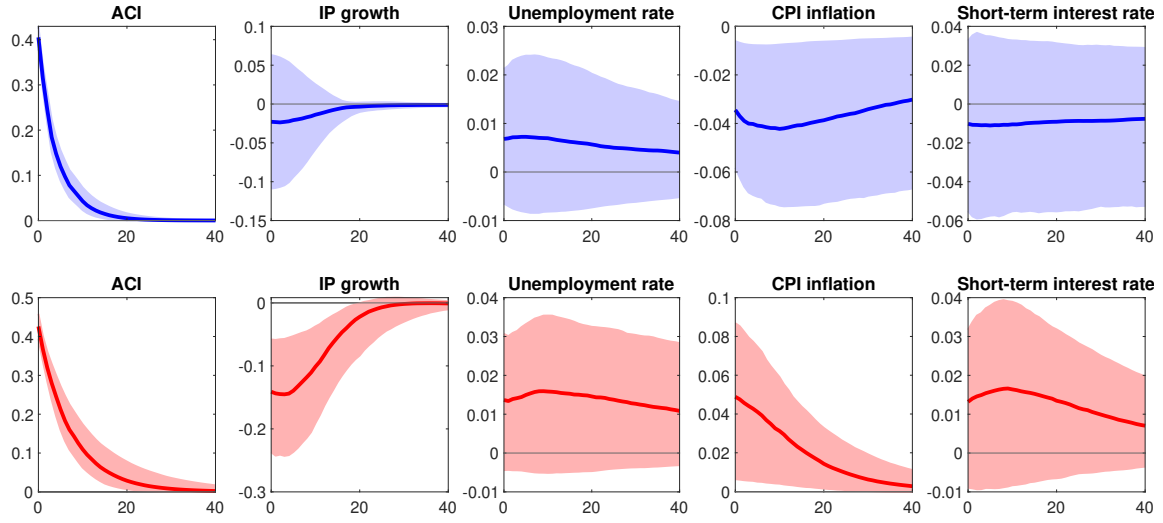


Figure 8: Results when we use a lagged moving average of ACI as our transition variable (choice (ii)).

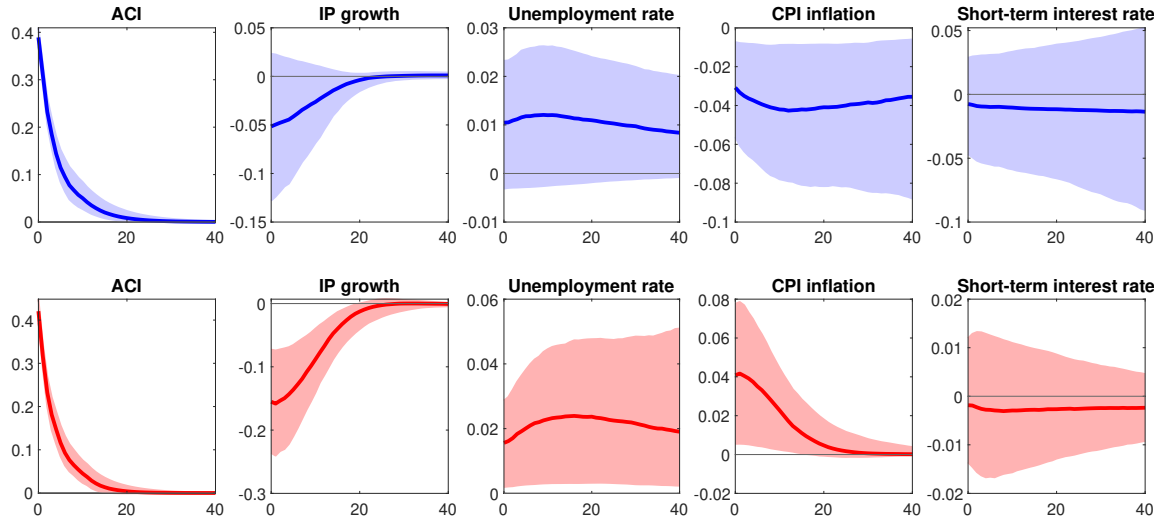


Figure 9: Results when we use a lagged moving average of CO2 concentration in the atmosphere as our transition variable (choice (iii)).

4.2 What Drives Our Results?

Since the ACI is made of six components, it is natural to ask what the effects of shocks to each specific component are. We thus repeat our exercise, adding one specific ACI component at a time to our set of variables (we thus run six additional VAR specifications). It is important to realize that the ACI components are not necessarily independent: to give one example, high temperatures and measures of drought certainly have some relationship). We relegate the full set of impulse responses to Appendix D and instead highlight findings here that directly relate to our benchmark results: (i) Precipitation has no effect on IP growth either at the beginning or the end of the sample but does increase unemployment when $\tilde{z}_t = 1$, (ii) the decrease in IP growth when $\tilde{z}_t = 1$ is driven by changes in both high and low temperatures, and (iii) sea level changes lead to changes in inflation consistent with those we see in our benchmark results.

5 Conclusion

We incorporate a novel index of extreme weather shocks into a VAR analysis of the United States macroeconomy and document that an increase in extreme weather leads to a persistent reduction in the growth rate of industrial production, a persistent increase in the unemployment rate, and a persistent increase in CPI inflation. Our findings suggest that increases in extreme weather can cause persistent (albeit modest) damages to economic growth and affect price stability even in a developed economy like the United States.

These findings will hopefully be useful to researchers building equilibrium models that incorporate climate change to both study policy responses and possible causes of the causal effects we have uncovered.

References

- Alvarez, J. L. C. and Rossi-Hansberg, E. (2021). The economic geography of global warming. Technical report, National Bureau of Economic Research.
- American Academy of Actuaries, Canadian Institute of Actuaries, Casualty Actuarial Society and Society of Actuaries (2020). Actuaries Climate Index.
- Auerbach, A. J. and Gorodnichenko, Y. (2012). Measuring the Output Responses to Fiscal Policy. *American Economic Journal: Economic Policy*, 4(2):1–27.
- Bakkensen, L. and Barrage, L. (2019). Climate shocks, cyclones, and economic growth: bridging the micro-macro gap. Technical report, Working paper.
- Bakkensen, L. A. and Mendelsohn, R. O. (2016). Risk and adaptation: Evidence from global hurricane damages and fatalities. *Journal of the Association of Environmental and Resource Economists*, 3(3):555–587.
- Barrage, L. and Furst, J. (2019). Housing investment, sea level rise, and climate change beliefs. *Economics letters*, 177:105–108.
- Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159.
- Batten, S., Sowerbutts, R., and Tanaka, M. (2020). Climate change: Macroeconomic impact and implications for monetary policy. *Ecological, Societal, and Technological Risks and the Financial Sector*, pages 13–38.
- Bognanni, M. and Herbst, E. (2018). A sequential Monte Carlo approach to inference in multiple-equation Markov-switching models. *Journal of Applied Econometrics*, 33(1):126–140.
- Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.

- Cachon, G. P., Gallino, S., and Olivares, M. (2012). Severe weather and automobile assembly productivity. *Columbia Business School Research Paper*, (12/37).
- Cameron, L. and Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. *Journal of Human Resources*, 50(2):484–515.
- Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561.
- Chang, Y., Kaufmann, R. K., Kim, C. S., Miller, J. I., Park, J. Y., and Park, S. (2020). Evaluating trends in time series of distributions: A spatial fingerprint of human effects on climate. *Journal of Econometrics*, 214(1):274–294. Annals Issue: Econometric Models of Climate Change.
- Cogley, T. and Sargent, T. J. (2002). Evolving Post-World War II U.S. Inflation Dynamics. In *NBER Macroeconomics Annual 2001, Volume 16*, NBER Chapters, pages 331–388. National Bureau of Economic Research, Inc.
- Colacito, R., Hoffmann, B., and Phan, T. (2019). Temperature and growth: A panel analysis of the united states. *Journal of Money, Credit and Banking*, 51(2-3):313–368.
- Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.
- Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3):740–98.
- Deryugina, T. and Hsiang, S. (2017). The marginal product of climate. Technical report, National Bureau of Economic Research.
- Diebold, F. X., Gobel, M., Coulombe, P. G., Rudebusch, G. D., and Zhang, B. (2020). Optimal Combination of Arctic Sea Ice Extent Measures: A Dynamic Factor Modeling Approach. Papers 2003.14276, arXiv.org.

- Emanuel, K., Sundararajan, R., and Williams, J. (2008). Hurricanes and global warming: Results from downscaling ipcc ar4 simulations. *Bulletin of the American Meteorological Society*, 89(3):347–368.
- Felbermayr, G. and Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of Development Economics*, 111:92–106.
- Giglio, S., Kelly, B. T., and Stroebel, J. (2020). Climate finance. Technical report, National Bureau of Economic Research.
- Golosov, M., Hassler, J., Krusell, P., and Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88.
- Graff Zivin, J. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.
- Granger, C. W. J. and Terasvirta, T. (1993). *Modelling Non-Linear Economic Relationships*. Number 9780198773207 in OUP Catalogue. Oxford University Press.
- Hassler, J. and Krusell, P. (2018). Environmental macroeconomics: The case of climate change. In *Handbook of Environmental Economics*, volume 4, pages 333–394. Elsevier.
- Herbst, E. P. and Schorfheide, F. (2016). *Bayesian Estimation of DSGE Models*. Number 10612 in Economics Books. Princeton University Press.
- Hong, H., Karolyi, G. A., and Scheinkman, J. A. (2020). Climate finance. *The Review of Financial Studies*, 33(3):1011–1023.
- Hornbeck, R. (2012). The enduring impact of the american dust bowl: Short-and long-run adjustments to environmental catastrophe. *American Economic Review*, 102(4):1477–1507.
- Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, 8:43–75.

- Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D., Muir-Wood, R., Wilson, P., Oppenheimer, M., et al. (2017). Estimating economic damage from climate change in the united states. *Science*, 356(6345):1362–1369.
- Hsiang, S. M. and Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research.
- Hsiang, S. M. and Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, 3(02):1250011.
- Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *Review of economics and statistics*, 87(2):271–284.
- Kishore, N., Marqués, D., Mahmud, A., Kiang, M. V., Rodriguez, I., Fuller, A., Ebner, P., Sorensen, C., Racy, F., Lemery, J., et al. (2018). Mortality in puerto rico after hurricane maria. *New England journal of medicine*, 379(2):162–170.
- Litterman, R. (1986). Forecasting with bayesian vector autoregressions-five years of experience. *Journal of Business and Economic Statistics*, 4(1):25–38.
- Ludvigson, S. C., Ma, S., and Ng, S. (2020). Covid19 and the macroeconomic effects of costly disasters. *NBER Working Paper*, (w26987).
- Mendelsohn, R. (2010). Climate change and economic growth. *Globalization and growth: Implications for a Post-Crisis World,” The International Bank for Reconstruction and Development*, pages 285–295.
- Mendelsohn, R., Emanuel, K., Chonabayashi, S., and Bakkensen, L. (2012). The impact of climate change on global tropical cyclone damage. *Nature climate change*, 2(3):205–209.
- Metcalf, G. E. and Stock, J. H. (2020). The macroeconomic impact of europe’s carbon taxes. Working Paper 27488, National Bureau of Economic Research.

- Nordhaus, W. (2014). *A Question of Balance: Weighing the Options on Global Warming Policies*. Yale University Press.
- Nordhaus, W. D. (1991). To Slow or Not to Slow: The Economics of the Greenhouse Effect. *Economic Journal*, 101(407):920–937.
- Nordhaus, W. D. (1993). Optimal greenhouse-gas reductions and tax policy in the "dice" model. *American Economic Review*, 83(2):313–317.
- Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2):221–231.
- Parker, M. (2018). The impact of disasters on inflation. *Economics of Disasters and Climate Change*, 2(1):21–48.
- Phan, T. and Schwartzman, F. (2021). Climate defaults and financial adaptation. *Working Paper*.
- Pretis, F., Schwarz, M., Tang, K., Haustein, K., and Allen, M. R. (2018). Uncertain impacts on economic growth when stabilizing global temperatures at 1.5 c or 2 c warming. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2119):20160460.
- Primiceri, G. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies*, 72(3):821–852.
- Roberts, M. J. and Schlenker, W. (2013). Identifying supply and demand elasticities of agricultural commodities: Implications for the us ethanol mandate. *American Economic Review*, 103(6):2265–95.
- Schelling, T. C. (1992). Some economics of global warming. *American Economic Review*, 82(1):1–14.
- Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1):1–48.

- Sims, C. A. and Zha, T. (2006). Were there regime switches in U.S. monetary policy? *American Economic Review*, 96(1):54–81.
- Smets, F. and Wouters, R. (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review*, 97(3):586–606.
- Stott, P. (2016). How climate change affects extreme weather events. *Science*, 352(6293):1517–1518.
- Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from us coastal counties. *Review of Economics and Statistics*, 93(2):575–589.
- Tran, B. R. and Wilson, D. J. (2020). The local economic impact of natural disasters. *Federal Reserve Bank of San Francisco Working Paper Series*.
- Von Peter, G., Von Dahlen, S., and Saxena, S. C. (2012). Unmitigated disasters? new evidence on the macroeconomic cost of natural catastrophes. *BIS working paper*.
- Waggoner, D. F., Wu, H., and Zha, T. (2016). Striated metropolis–hastings sampler for high-dimensional models. *Journal of Econometrics*, 192(2):406–420.
- Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.

A Data

This section provides details of our data sources used in the paper.

Actuaries Climate Index

As described in the main text, we use the continental United States data for both aggregate ACI and each of the six components of the ACI. The data is monthly frequency from 1963.04 to 2019.05. The dataset is accessible for free at <https://actuariesclimateindex.org/>. For detailed descriptions, see <https://actuariesclimateindex.org/wp-content/uploads/2019/05/ACI.DevDes.2.20.pdf>.

Benchmark Macro Variables

We use the following variables for the period 1963.04 to 2019.05.

- *Industrial Production Growth*: We obtain seasonally adjusted industrial production from <https://fred.stlouisfed.org/series/INDPRO> and calculate year-on-year growth rate.
- *Consumer Price Index Inflation*: We obtain seasonally adjusted consumer price index from <https://fred.stlouisfed.org/series/CPIAUCSL> and calculate year-on-year growth rate.
- *Effective Federal Funds Rate*: We obtain from <https://fred.stlouisfed.org/series/FEDFUNDS>, which is not seasonally adjusted. For the zero lower bound duration, we replace the federal funds rate with the Wu-Xia shadow rate (<https://www.frbatlanta.org/cqer/research/wu-xia-shadow-federal-funds-rate?panel=2>), which captures the hypothetical monetary policy rates going below the zero lower bound. The full details of the Wu-Xia shadow rate are provided in Wu and Xia (2016).
- *Unemployment Rate*: We obtain from <https://fred.stlouisfed.org/series/UNRATE>, which is seasonally adjusted.

- *Core Consumer Price Index inflation*: We obtain seasonally adjusted core CPI from <https://fred.stlouisfed.org/series/CPILFESL> and calculate year-on-year growth rate for the same period in the benchmark variables.

B Bayesian Inference and Priors

B.1 Priors

We use Gaussian priors throughout our analysis. The priors for the intercept are centered at the point estimate for our training sample with a standard deviation of 1. The prior for the elements of Σ are centered at the values obtained from the Cholesky decomposition of the covariance matrix of the one-step ahead forecast error from our training sample OLS estimation. The standard deviations are set at 0.25. The priors for the A_ℓ matrices are set using a Minnesota prior as in [Litterman \(1986\)](#), with the parameters $\lambda = 0.1$ and $\theta = 0.01$ (using Litterman’s notation).

B.2 Bayesian Inference

We use a sequential Monte Carlo (SMC) method to approximate the posterior (see [Herbst and Schorfheide \(2016\)](#) and [Bognanni and Herbst \(2018\)](#)). We track 100,000 particles as we move in 100 steps from the prior to the posterior. We use a quadratic function ($\lambda = 2$ in the notation of [Herbst and Schorfheide \(2016\)](#)) to govern the weight on the likelihood function at each iteration of the algorithm. In the mutation step of the algorithm, we use five iterations of the Metropolis-Hastings algorithm.

C The Effects of Seasonal Adjustment

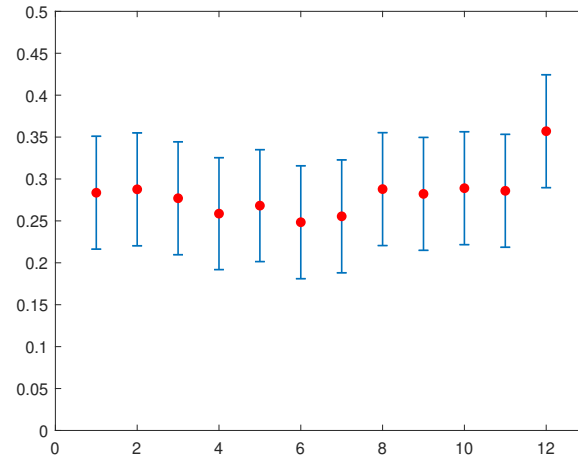


Figure C.1: Regression coefficients of seasonally adjusted ACI on 12 monthly dummies (error bands cover ± 1 standard deviation).

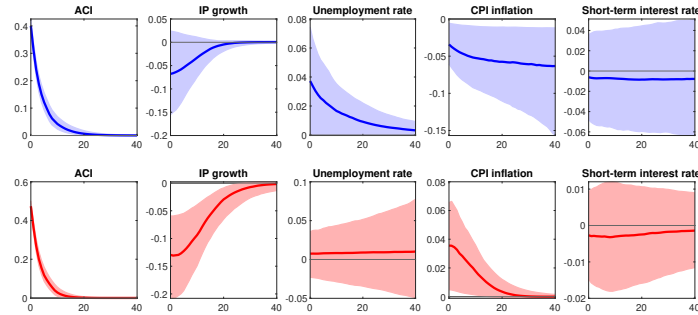


Figure C.2: Results with non-seasonally adjusted data.

D Shocks to Components of ACI

One feature of these impulse responses not discussed in the main text that we think is worthwhile pointing out is the positive effect on IP growth that droughts (D) seem to have. We can identify three possible channels to explain this: (i) droughts will hit agricultural production, but that is not a part of industrial production, (ii) there is a slight endogenous lowering of interest rates that can counteract negative effects on IP growth, and (iii) industrial production might rise endogenously as, for example, farmers in part of the country not hit by the drought need to acquire more machines to deal with larger demand for their goods.

Concerning the response of T10, note that this measure enters negatively into the overall ACI index, as discussed in the main text. Thus, a positive T10 shock decreases the ACI as low temperatures increase. We find that such a decrease in the ACI has expansionary effects on IP growth.

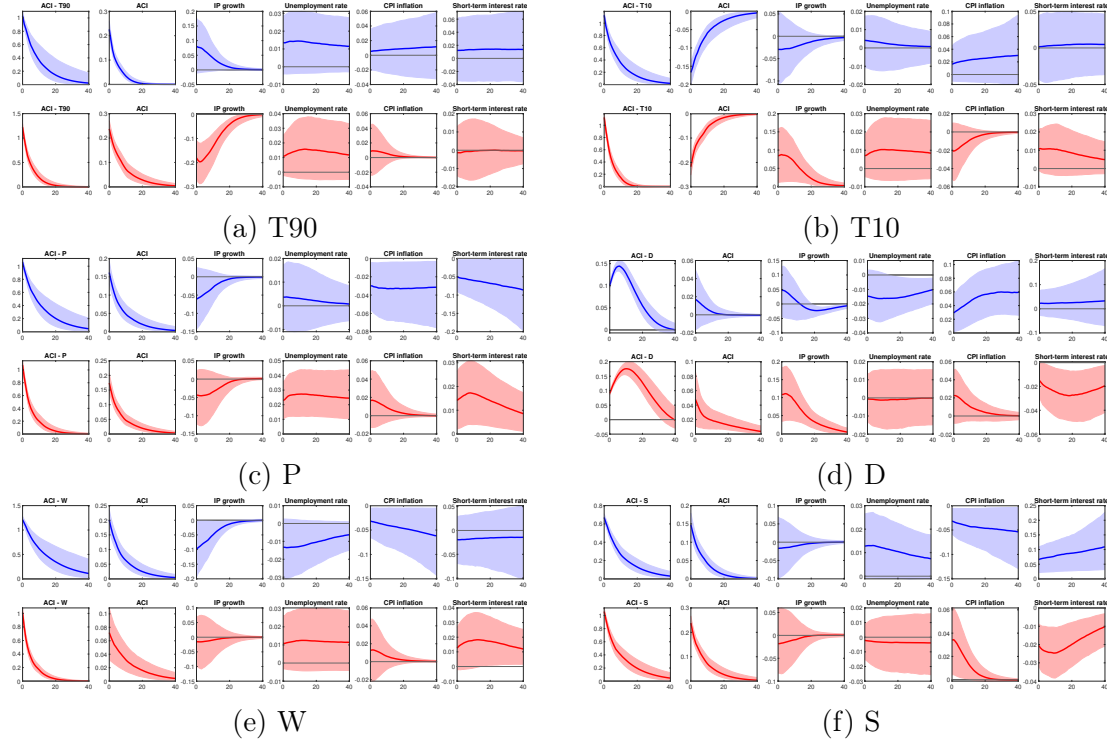


Figure D.3: Component analysis