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Severe Weather and the Macroeconomy

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Abstract

We investigate the impacts of severe weather shocks on the U.S. macroeconomy over the past sixty years. Using a smooth transition vector autoregressive model, we find robust evidence of time-varying effects. While negligible at the beginning of the sample, the impacts become significant at the end, where an increase in the severe weather index reduces aggregate industrial production and consumption *growth* rates, and raises aggregate unemployment and inflation rates. The effects are persistent up to 20 months. Our findings suggest limited adaptation to increased severe weather in the U.S., at least at the macroeconomic level.

Keywords: severe weather, STVAR, growth, inflation

JEL codes: E23, Q54

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1 Introduction

How do severe weather shocks affect the macroeconomy? Have the effects changed over time? We address these questions by employing a flexible empirical macroeconomic approach (smooth transition vector autoregression) that allows for time-varying weather distributions with time-varying economic effects, applied to high-frequency macroeconomic data for the United States between 1963 and 2019 combined with a recently developed meteorological time series for severe weather.

The investigation of the economic effects of weather and climate-related shocks has been the focus of a large and growing body of research (see the related literature section below). A general challenge facing the literature estimating the effects of weather shocks, whose underlying distribution is changing through time (due to climate change), on the macroeconomy, where agents may be adapting to such changes through time (via taking adaptive actions, such as investing in infrastructure or production technologies that are more resilient to bad weather shocks, which are generally unobservable at the macro level). To address this challenge, we adopt the benchmark vector autoregressive (VAR) analysis, which is a workhorse model in empirical macroeconomics (e.g., Sims 1980; Christiano et al. 2005; Beaudry and Portier 2006; Brunnermeier et al. 2021a), but explicitly allow for time-variation in the distribution and effects of weather shocks to potentially incorporate both climate change (time-varying distribution) and adaptation (time-varying coefficients). We could identify the time variation in various ways. For example, we could simply split the sample into an earlier and a later subsample and run the estimations separately for each of them.[1] However, we might lose useful variation over time by splitting

[1] This method was adopted, for example, in an influential work by Barreca et al. (2016).

the sample. Instead, to more efficiently exploit all available data in our estimation, we employ a smooth transition VAR (STVAR) as pioneered by Auerbach and Gorodnichenko (2012). In a STVAR, the parameters are determined as a convex combination of two sets of parameters, with weights being a function of a predetermined observable, which we set to be time. Consequently, we explicitly allow for the parameters that govern the distribution as well as the economic effects of weather shocks to potentially vary across time, and we can formally evaluate the effects of climate change in the presence of adaptation.

We apply the econometric framework to the US economy, employing standard macroeconomic data combined with a recently developed meteorological time series for severe weather – the Actuaries Climate Index or ACI. We find robust evidence of time-varying macroeconomic effects of weather shocks. A shock to the ACI index had no statistically significant effects at the beginning of the sample (when the severe weather index is lower on average) but led to significant effects at the end of the sample (when the severe weather index is higher on average). Specifically, a transitory one-standard-deviation increase in the severe weather index is associated with a decline in the *growth rate* of aggregate industrial output and aggregate consumption and a increase in aggregate unemployment and the inflation rate at the end of the sample. The effects are persistent for up to about 20 months.

The fact that the economic effects of an ACI shock of similar magnitude is stronger in the more recent part of the sample suggests that there is not sufficient adaptation in the US economy to the changing distribution of weather shocks. This echoes findings in a growing empirical literature on climate adaptation, which finds rather mixed evidence of adaptation in the United States

There, the authors identify adaptation by asking whether the elasticity of US mortality to extreme heat is lower in the recent sample compared to that in the earlier sample.

(e.g., Hornbeck 2012; Burke and Emerick 2016; Bakkensen and Mendelsohn 2016; Barrage and Furst 2019).

Our findings on the effects of severe 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 (e.g., Parker 2018), the concern that climate-related shocks may affect price stability has been revived in recent policy discussions among advanced countries' central banks.[2] Our evidence suggests that severe weather does have a statistically significant and persistent effect on inflation, though the effects are moderate in magnitude and are driven by the responses of food and energy prices.

Related literature. Our paper is related to a large and growing empirical literature that aims to estimate the (macro)economic effects of weather shocks and climate change (e.g., see Dell et al. 2012, 2014; Hsiang 2016; Colacito et al. 2019 and references therein). Our paper is especially related to the growing literature that applies modern econometric methods to study weather shocks, climate change, and the associated economic effects (see, e.g., Pretis et al. 2018, Chang et al. 2020, Diebold et al. 2020, Metcalf and Stock 2020, Berg et al. 2021, and Kiley 2021). While earlier works have documented substantial negative effects of weather and climate-related shocks on economic growth in

[2]For example, the European Central Bank (ECB) officially stated on July 8, 2021, their plan to incorporate climate change considerations into their 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 severe 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"). The Bank of England also issued similar statements (Batten et al. 2020).

developing countries (e.g., see Dell et al. 2012; Von Peter et al. 2012; Bakkensen and Barrage 2019; Mumtaz and Alessandri 2021),[3] it has been more challenging to provide systematic evidence that weather shocks can affect the aggregate macroeconomy in developed economies like the U.S., 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 U.S. has focused on subsections of the economy that are naturally exposed to outdoor weather conditions.[4] We contribute to this literature by providing evidence that weather shocks do affect the US economy, *even at the aggregate national level*, and even for the production of industrial sectors that are generally less exposed to outdoor weather (compared to agriculture).

Furthermore, in the macroeconomic literature, natural disaster shocks are typically thought to have short-lived effects in the U.S., or they may even stimulate local economic growth as the economies rebuild from the disaster (e.g., the "build back better" finding in the local county-level analysis in Tran and Wilson 2022). Our findings suggest a different picture at the aggregate national level: severe weather shocks have persistent damages on aggregate IP growth. In fact, our result resonates with the "no recovery" finding in Hsiang

[3]See the related literature on natural disasters and growth, which have found mixed results, with some papers suggesting limited, no effects, or even positive effects on local economic growth while others documenting very persistent growth damages at the macro level (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 2022). Also see Ludvigson et al. (2020), which compares the effects of billion-dollar natural disasters against the effects of the COVID-19 epidemic in the U.S., and Davis and Ng (2021), which uses VARs to identify disaster shocks.

[4]E.g., see Roberts and Schlenker (2013), Burke and Emerick (2016) and references therein for evidence of weather effects on US 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 US 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.

and Jina (2014), which document very persistent damages of cyclone shocks on GDP growth in a panel of countries (including many small and developing nations), even though as expected, our estimated effects are smaller and less persistent.[5] One possible reason for why disaster recovery could be generally faster at the local level than at the national level is the inflows of federal disaster aid to affected localities, which would speed up the rebuilding process. These transfers, however, would show up with a fiscal cost at the national level (Deryugina 2017; Barrage 2020). An advantage of our aggregate analysis is that by looking at macroeconomic time series, it naturally takes into account these aggregate costs of fiscal policies and more broadly spatial and general equilibrium responses to shocks.[6]

The rest of the paper is organized as follows. Section 2 describes the econometric model. Section 3 describes the data. Section 4 provides the results. Section 5 provides robustness checks and further discussions, and Section 6 concludes.

2 Econometric Model: A Smooth Transition VAR

To analyze the effects of weather shocks while allowing for structural change, 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

[5] For instance, while a severe weather shock reduces IP growth in the United States for about 20 months at the end of our sample, Hsiang and Jina (2014) find that a cyclone shock reduces GDP per capita growth in a panel of countries, which include both developing and developed nations, for about 20 years.

[6] See Remark 1 on page 16 for a further discussion.

in VARs (see, for example, Cogley and Sargent 2002, Primiceri 2005, or Sims and Zha 2006), we choose this form because it makes the way parameters change transparent, and it fits nicely with our economic question: are the effects of severe weather events different now than they were decades ago (as a consequence of climate change and adaptation)?[7]

As is common in empirical macroeconomics, we jointly model the evolution of all variables of interest to fully capture general equilibrium feedback effects. To do so, we stack all observable variables of interest (the ACI as well as various economic outcomes) at time t in a column vector $\mathbf{y}_t$. We order ACI first in $\mathbf{y}_t$.

The idea behind STVARs is straightforward: assume there are two sets of parameter values $(\{\mathbf{m}_j, \{\mathbf{A}_{\ell,j}\}_{\ell=1}^{\mathcal{L}}, \boldsymbol{\Sigma}_j\}_{j=1,2})$, and at each point in time the dynamics are governed by a convex combination of these two. We will call parameters with a subscript of 1 beginning-of-sample parameters and those with a subscript of 2 end-of-sample parameters. The weights for the convex combination are determined by a transition variable $\tilde{z}_{t-1}$ (specified below), leading to the following VAR equation that governs the evolution of y_t:

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

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 (a shock to the ACI). For the transition variable $\tilde{z}_{t-1}$, we use a simple time-dependent transition:

$$\tilde{z}_t := \frac{t}{T}, \quad \forall 0 \leq t \leq T. \quad (2)$$

[7] The aforementioned other models of time-varying parameters might accidentally pick up higher frequency changes in the relationships between our variables, such as changes in the monetary transmission mechanism.

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. Intuitively, equation (1) states that at the beginning of the sample, the dynamic relationship between macroeconomic variables and the ACI is governed by parameters $\{\mathbf{m}_1, \{\mathbf{A}_{\ell,1}\}_{\ell=1}^{\mathcal{L}}\}$, while at the end of the sample, the dynamics are governed by a potentially different set of parameters $\{\mathbf{m}_2, \{\mathbf{A}_{\ell,2}\}_{\ell=1}^{\mathcal{L}}\}$. The estimates for the first parameter set would inform us of the effects of weather shocks on economic variables at the beginning of the sample. Similarly, the estimates for the second set would inform us of such effects at the end of the sample. The difference in the estimates for these parameter sets would inform us of the effects of the changes in the distribution of weather shocks due to climate change and climate adaptation in our data.

The parameters $\{\mathbf{m}_j, \{\mathbf{A}_{\ell,j}\}_{\ell=1}^{\mathcal{L}}\}$ in (1) determine the one period ahead expectations $E_t\mathbf{y}_{t+1}$ as a function of $\mathcal{L}$ lags of $\mathbf{y}_{t+1}$. With monthly data, we use twelve lags ($\mathcal{L} = 12$). The parameter matrices $\mathbf{\Sigma}_1$ and $\mathbf{\Sigma}_2$ encode how both economic variables as well as the ACI itself react on impact (i.e., within the same period) to an unexpected change (i.e., a shock) in various variables. We will specifically be interested in one column of these matrices – the column that tells us how all variables react to ACI shocks. Note that different values of $\mathbf{\Sigma}_1$ and $\mathbf{\Sigma}_2$ will deliver the same first and second moments conditional on past data and hence the same value of the Gaussian likelihood function.[8] This is the common identification problem in VARs. Below we discuss restrictions on $\mathbf{\Sigma}_1$ and $\mathbf{\Sigma}_2$ that allow us to uniquely pin down the impact effect of an ACI shock on the system as described by equation (1). Once we have the

[8] More specifically, all matrices $\tilde{\mathbf{\Sigma}}_1$ such that $\tilde{\mathbf{\Sigma}}_1\tilde{\mathbf{\Sigma}}_1' = \mathbf{U}_1$ for some positive semidefinite matrix $\mathbf{U}_1$ and all matrices $\tilde{\mathbf{\Sigma}}_2$ such that $\tilde{\mathbf{\Sigma}}_2\tilde{\mathbf{\Sigma}}_2' = \mathbf{U}_2$ for some positive semidefinite matrix $\mathbf{U}_2$ will deliver the same variance of one-step ahead forecast errors.

impact effect in hand, we can trace out the effects of an unexpected change in ACI over time using the same equation because our model fully describes the dynamics of all variables we are interested in once we determine the dynamics of $\tilde{z}_t$, which we turn to next.

We use a Bayesian approach throughout.[9] The priors we use are described in detail in Appendix A.2. Broadly speaking, we use standard Minnesota-type priors (Litterman, 1986) for $\{A_{\ell,j}\}_{\ell=1}^{\mathcal{L}}$. 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).[10] We relegate the details to Appendix A.2.

Our *key identification assumption* is that economic shocks do not have contemporaneous effects on the ACI. Any unexpected changes in the economy from one month to the next are thus assumed to have no influence on the

[9]One advantage of this estimation approach is that it remains valid independently of whether or not the data has unit roots (Sims and Uhlig, 1991).

[10]See also Waggoner et al. (2016) for a similar algorithm.

occurrence of severe 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, we define the one-step ahead forecast error implied by equation (1) as $\mathbf{u}_t := \mathbf{y}_t - E_{t-1}\mathbf{y}_t = ((1-\tilde{z}_t)\mathbf{\Sigma_1} + \tilde{z}_t\mathbf{\Sigma_2})\mathbf{e}_t$. 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 matrices $\mathbf{\Sigma}_1$ and $\mathbf{\Sigma}_2$. For parsimony, we define $\mathbf{\Sigma}_t = (1-\tilde{z}_t)\mathbf{\Sigma_1} + \tilde{z}_t\mathbf{\Sigma_2}$. This allows us to state our identification restriction as follows: the first element of $\mathbf{u}_t$ is equal to a constant $\mathbf{\Sigma}_t^{11}$ (the element in the first row and first column of $\mathbf{\Sigma}_t$) times the first element of $\mathbf{e}_t$. This restriction implies that all elements in the first row of $\mathbf{\Sigma}_t$ except for the very first element $\mathbf{\Sigma}_t^{11}$ 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 identification of all elements of $\mathbf{\Sigma}_t$, we assume that $\mathbf{\Sigma_1}$ and $\mathbf{\Sigma_2}$ (and thus $\mathbf{\Sigma}_t$) are lower triangular for all t. 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 $\mathbf{\Sigma}_t$ 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 $\mathbf{\Sigma}_t$.

3 Data

3.1 The Actuaries Climate Index (ACI)

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 severe weather and the extent of sea level rise. We use the monthly ACI index for the U.S. between 1963.04 and 2019.05. The ACI index consists of the following six components:

1. High temperatures ($T90$), which tracks the change in the frequency of temperatures above the 90th percentile relative to the reference period (1961 to 1990).

2. Low temperatures ($T10$), 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).

The first five elements are based on gridded data (at the resolution of 2.5 by 2.5 degrees latitude and longitude), and the last element of sea level rise is based on tidal gauge station data. The aggregation to the regional[11] and national level is done in the following steps. First, to harmonize the units of measurement across various weather variables at various locations, the raw observations at each grid point is transformed into a standardized anomaly. As usual, the standardized anomaly $X_{i,t}^{std}$ of a weather variable (say, temperature) X at location i and time t (e.g., Jan 2010) is calculated as $\frac{X_{i,t}-\mu_{X,i}^{1961-1990}}{\sigma_{X,i}^{1961-1990}}$, i.e., the difference between the current observation and the average of X at location i for the same month (e.g., Jan) during the reference period of 1961-1990, and then scaled by the division of its reference period standard deviation. Second, the percentiles in $T90, T10$, and W are defined at each grid point, calculated based on the distribution of the standardized anomaly temperature or wind observed at each grid point in the 1961-1990 reference period. Third, to aggregate to the regional or national level, each of the variables is then averaged across all the stations on the grid (or all the coastal stations for the sea level rise component) within a region or within the continental United States. This yields six aggregate time series $T90_t^{std}$, $T10_t^{std}$, P_t^{std}, D_t^{std}, W_t^{std}, and S_t^{std}. The ACI is then defined as:

$$ACI_t = mean(T90_t^{std} - T10_t^{std} + P_t^{std} + D_t^{std} + W_t^{std} + S_t^{std}).$$

Note that the sign of $T10_t^{std}$ is negative to reflect the fact that severe cold days are less likely due to the recent warming trends in temperatures.[12] We provide

[11]The sub-national regions are ALA (Alaska), CEA (Central East Atlantic), CWP (Central West Pacific), MID (Midwest), SEA (Southeast Atlantic), SPL (Southern Plains), and SWP (Southwest Pacific).

[12]According to the ACI documentation, a justification for the negative sign of $T10_t^{std}$ is: "As temperatures are warming over the United States and Canada in recent decades, T10 is

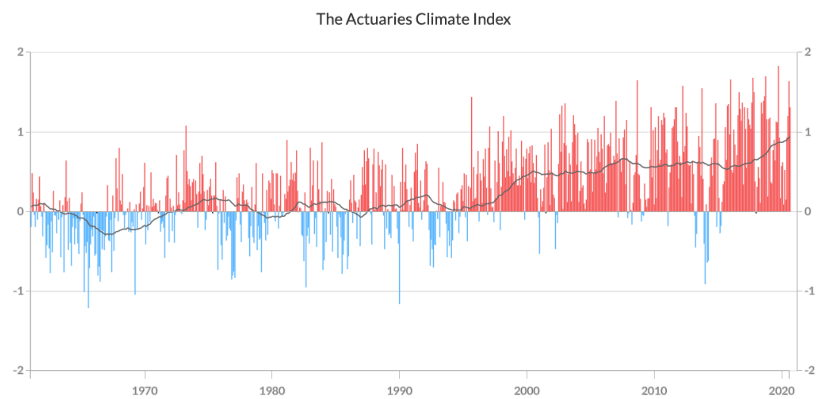
several robustness checks to this definition in Section 5, including a principle component analysis of the six components as an alternative way to combine the six components, an analysis of each component individually, and another analysis where we exclude $T10_t^{std}$.

	ACI	T90	T10	P	D	W	S
First subsample: 1963m4 - 1990m12							
Mean	0.0104	0.0068	-0.0069	0.0151	-0.0292	0.0070	0.0555
Variance	0.1521	0.9389	0.8469	0.8121	1.0689	0.9146	0.9115
Second subsample: 1991m1-2019m5							
Mean	0.5466	0.7197	-0.5990	0.3252	0.2167	-0.2387	1.6576
Variance	0.2050	1.2524	0.8966	0.8465	1.3334	0.7497	1.3148

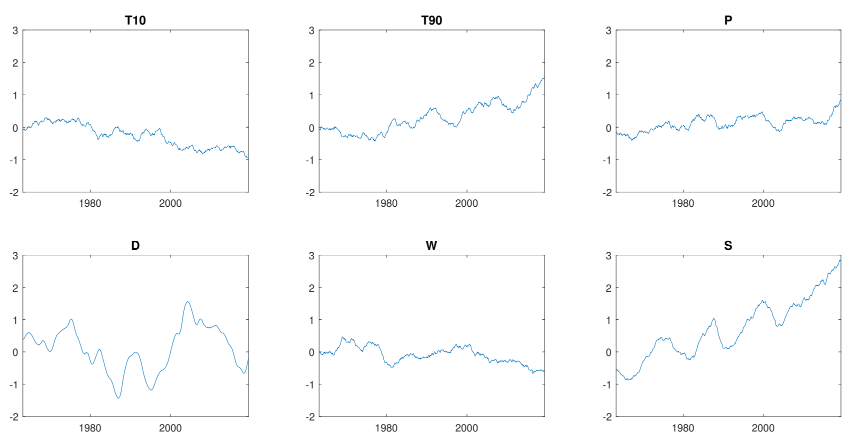
Table 1: Means and variances of ACI and its (seasonally adjusted and standardized) components.

Table 1 provides the first and second moments of the ACI and its standardized six components over two subsamples. We can see that the average values of the ACI and its components have noticeably increased (decreased for $T10$ and W) over time, suggesting that the severe weather activities have generally increased over time.

generally less than it was during the reference period; i.e., the change is a negative number, while the change in T90 is generally a positive number. To properly reflect this change in the temperature distribution, the sign of T10 is reversed in the Actuaries Climate Index to properly reflect its contribution to this shift. 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."



(a) 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.



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

Figure 1: The Actuaries Climate Index (ACI)

Figure 1a plots the ACI for the continental United States, and Figure 1b plots the corresponding standardized six components. Note that there is noticeably higher volatility in the ACI compared to other economic variables – this high variation is useful for us in identifying the economic effects of severe weather shocks. Also note that the ACI is on average higher at the end of the sample, suggesting that the severe weather has gradually increased over the past decades.

3.2 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)[13], 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 severe weather can influence outcomes (Nordhaus, 1991). Hence, our estimated effects on industrial production provide a lower bound on the overall real effects of severe weather. We provide further descriptions of our data sources in Appendix A.1. 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 2 plots the seasonally adjusted time series of the variables employed in our empirical analysis: the ACI for the United States, IP growth, CPI and core CPI inflation, short-term interest rate, and unemployment rate. In Section 5.6, we both show that our seasonal

[13] During and after the financial crisis, we use the Wu and Xia (2016) shadow rate.

adjustment does indeed remove the seasonal patterns in the ACI index, but that our results are also robust to using nonseasonally adjusted data (for both the ACI and the macroeconomic variables we study).

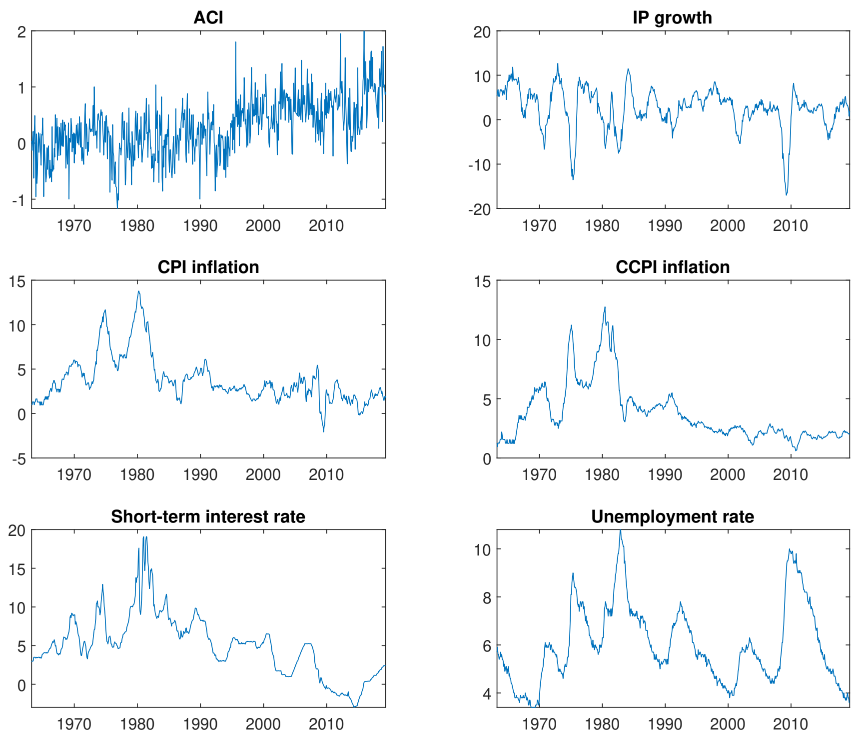


Figure 2: US monthly time series used for empirical analysis: the Actuaries Climate Index (ACI), year-on-year Industrial Production (IP) growth, year-on-year Consumer Price Index (CPI) inflation, Core CPI inflation, short-term interest rate, and unemployment rate.

Remark 1. Before moving on to the results, it may be useful to discuss the pros and cons of our VAR approach using macro data versus the panel approach using subnational data adopted in the earlier literature (e.g., Deryugina and Hsiang 2017; Colacito et al. 2019). The panel approach with time fixed effects can better identify the effects of local weather shocks on the local economy. However, a drawback of this approach is that it will miss out on general equilibrium and spillover effects, which in that approach gets soaked up in time fixed effects. Those effects, instead, will be captured in the VAR approach with macro data because we jointly model the dynamics of all variables of interest. As a specific example, consider a panel regression of climate-related disaster shocks on the local economy at the county level (e.g., as in Tran and Wilson 2022). Suppose it finds that such shocks have limited (or even positive) effects on the local economy, due to injections of funds from insurance claims and aid from the state and federal levels in the aftermath of the disaster. However, it would be misleading to infer from this result that disasters have limited (or even positive) effects on the aggregate national economy. This is because insurance claims will show up as a cost to insurance firms; similarly, disaster aid will show up as fiscal cost to the government (e.g., Deryugina 2017; Barrage 2020). Another general equilibrium/indirect effect that the local estimate will likely miss out is that asset prices in vulnerable, but not directly affected areas, can still respond to news about the disaster. As a specific example, Addoum et al. (2021) documented that coastal housing prices in Boston are negatively affected by Hurricane Sandy, even in the absence of direct damages (the hurricane only struck New York and New Jersey). The reasoning is because the hurricane increases the salience of climate-related risks to which coastal Boston properties are exposed to. An advantage of using macroeconomic data is that macroeconomic variables track economic changes not only at the local level but also at the national level (including changes in insurance sector expenditure and government spending, as well as changes in economic activities due to movement in housing prices, in the aforementioned examples). Hence, the approach that we employ can arguably capture such general equilibrium and spillover effects better.

4 Results

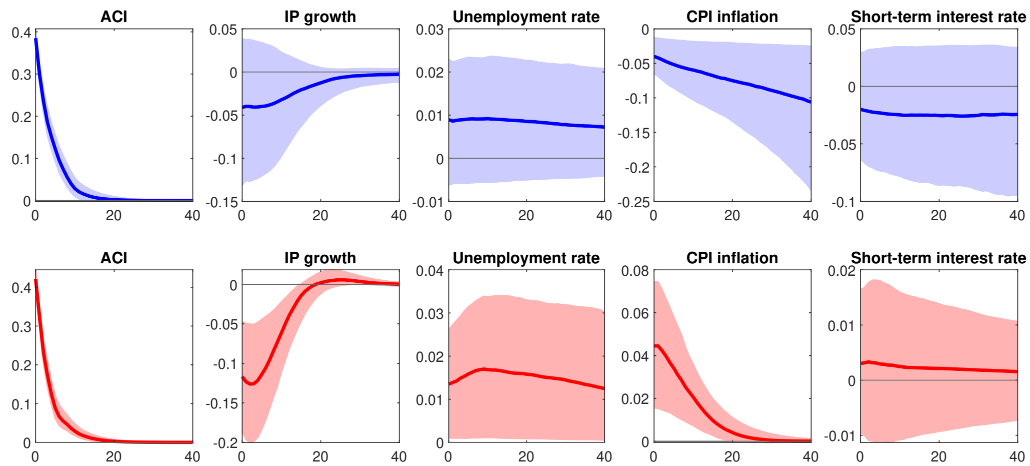


Figure 3: Main results: Impulse responses of macro variables (columns 2 to 5) to a one-standard-deviation shock to the ACI (column 1). Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

Our main results are as follows. Figure 3 plots the impulse response functions (IRFs) of macro variables to a one-time one-standard-deviation shock to the ACI.[14] 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.

The first column of Figure 3 shows the one-standard-deviation shocks to the ACI at the beginning and end of the sample. The column suggests that while the average of the ACI series does increase noticeably over time (as seen

[14]To 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).

in Figure 1a), the volatility of its forecast error does not change over time.

Industrial Production The second column of Figure 3 reports the responses of the year-over-year IP growth to the ACI shock. The ACI shock has no statistically significant effect at the beginning of the sample.[15] 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 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.

The persistent damage on IP growth would compound to 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 4 plots the corresponding impulse 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 preshock trend even after 40 months.[16]

[15]Throughout, we use "statistical significance" to indicate whether the posterior bands include zero or not.

[16]We also estimated a VAR with month/month IP growth rates and then accumulated up the IP growth responses. The results are very similar and are omitted for brevity.

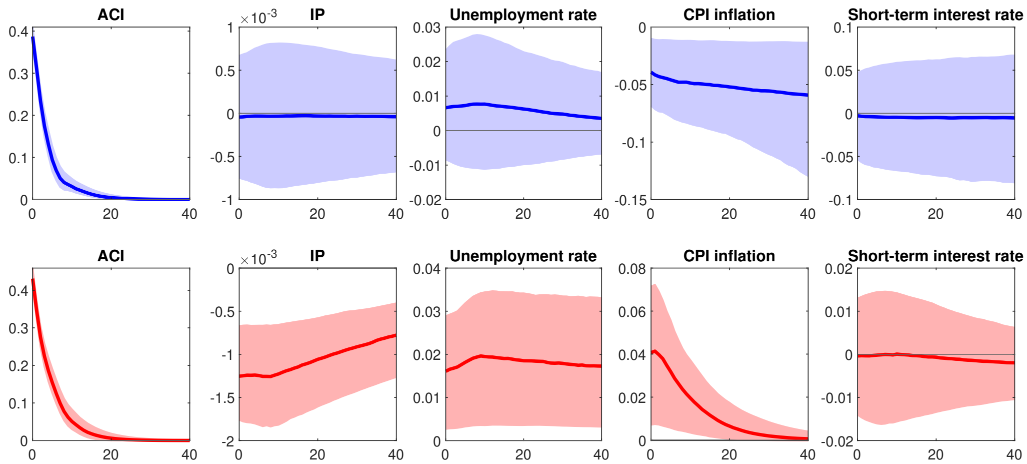


Figure 4: Log of IP level instead of IP growth. Impulse responses of macro variables to a one-standard-deviation shock to the ACI. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months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

Our finding also suggests that there is nonlinearity in the economic effects of weather shocks.[17] Recall from Figure 2 that the average ACI level at the end of the sample is higher than that at the beginning. Figure 3 suggests that the increase in the ACI from a higher level has a stronger damage on growth.

The finding also suggests that there has been limited adaptation to increased severe weather over the years of our sample, at least at the macroeconomic level. 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 echoes existing papers in the climate adaptation literature, which so far have found mixed evidence for adaptation in the U.S. (e.g., Hornbeck 2012; Burke and Emerick 2016; Mendelsohn et al. 2012; Bakkensen and Mendelsohn 2016; Barreca et al. 2016).[18]

[17]This echoes the well-documented nonlinear economic effects of weather shocks (e.g., see Burke et al. 2015 in the global context and Hsiang et al. 2017 in the US context).

[18]For example, Barreca et al. (2016) documented that the U.S. has adapted to the effects

Unemployment Returning to our benchmark results in Figure 3, the effect on the unemployment rate reported in the third column is similar to the effect on IP growth in that the effects become more severe over time, although error bands are much wider compared to IP. 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.

Inflation Turning toward nominal variables in Figure 3, the fourth column shows that the ACI 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 5 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. The Federal Reserve

of extreme heat on mortality via the adoption of air conditioning. Gourio and Fries (2020) argued that economic activities have adapted heterogeneously across the U.S. to rising temperatures. However, despite the widespread adoption of air conditioning in the U.S., Cachon et al. (2012) found that high temperatures decrease productivity and performance in the US automobile sector, and Graff Zivin and Neidell (2014) found large reductions in time allocated to labor in industries that are exposed to weather conditions. Burke and Emerick (2016) found little to no evidence for adaptation to the changes in temperature and precipitation in the US agriculture sector. Hsiang and Narita (2012), Bakkensen and Mendelsohn (2016), and Bakkensen and Barrage (2019) argue that there is little adaptation to hurricanes in the U.S., as the estimated marginal economic damage and marginal increase in fatality from hurricane wind speed is exceptionally high for the U.S., when compared to those from other developed countries. It remains an open research question as to why this is the case. For instance, Barrage and Furst (2019) document that the potential role of climate belief heterogeneity, which is very pronounced in the U.S.: the elasticity of coastal housing investment to sea level rise-induced flood risk critically depends on the fraction of local county residents who believe that climate change is happening.

usually focuses on movements in measures of core inflation when setting their monetary policy. This is reflected in our estimated response of the nominal interest rate, which does not move in any meaningful way after a severe weather shock.

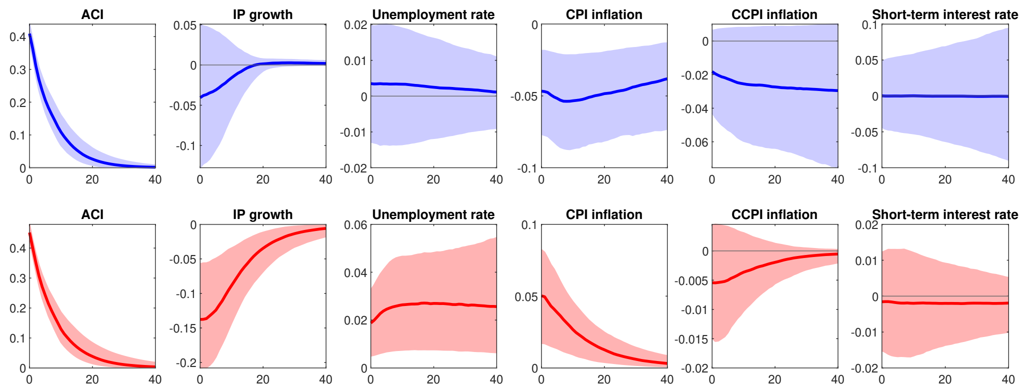


Figure 5: CPI and Core CPI: Impulse responses of inflation, core inflation, and other macro variables to a one-standard-deviation shock to the ACI. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

The last column of Figure 3 shows that the ACI shock appears to have no statistically significant effect on the short-term interest rate, which is intuitive because we do not expect monetary policy to react directly to movements in the ACI (e.g., Keen and Pakko 2011).

Economic Significance To assess the economic significance of our main estimates in Figure 3, 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) as shown in Table 2. 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, Smets and Wouters (2007)'s well-known DSGE model attributes less than 10 percent of fluctuations in GDP and inflation at its point estimate to monetary policy shocks at similar horizons.

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 2: Variance decomposition (using 1000 draws).

Aggregate Consumption A potential concern is that industrial production only accounts for a part of total GDP. Ideally we would thus like to include GDP directly into our model. GDP is, however, not available at a monthly frequency.[19] There is, however, one component of real GDP that we can

[19]GDP is only available at a quarterly frequency. Since unexpected movements in the ACI are relatively short-lived (as our benchmark results how), aggregating to a quarterly frequency would result in meaningful temporal aggregation bias. Monthly estimates of real

get official statistics at a monthly frequency: Aggregate consumption. In particular, we use the Personal Consumption Expenditures (PCE) series from the St. Louis Fed's FRED database.[20] Consumption expenditures account for over 60 percent of GDP on average for our sample.

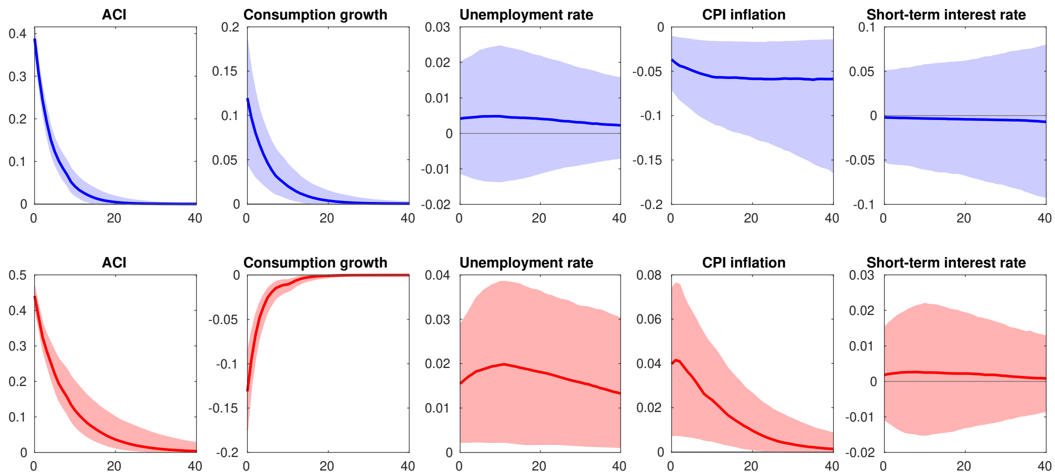


Figure 6: Impulse responses to a one-standard deviation shock to ACI. In this figure, IP growth has been replaced by real aggregate consumption growth in the second column. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

We repeat our main analysis but replace the IP growth series with the aggregate consumption growth series. Figure 6 shows that our original finding carries over: the weather shock leads to a persistent decline in aggregate consumption growth. In short, our results suggest that in the more recent sample, severe weather shocks have nontrivial detrimental effects on the macroeconomy.

GDP are inherently noisy and dependent on the specifics of an auxiliary model used to turn quarterly GDP data and monthly observations on real activity into an estimate of monthly GDP. Furthermore, since these estimates rely crucially on monthly indicators of real activity, they are very much informed by IP and unemployment rate data, two variables we already used in our setup.

[20] Retrieved from https://fred.stlouisfed.org/series/DPCERE1Q156NBEA.

5 Discussions and Robustness Checks

5.1 Splitting the Sample

In this section, we study an alternative choice for $\tilde{z}_t$: 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. Figure A.1 shows that even when we completely disregard any information from the benchmark 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 by noncore components of inflation anyway.

5.2 ACI Principal Component Analysis

To evaluate whether our results are robust to how the aggregate weather variable is constructed, we now provide a principal component analysis as an alternative approach to aggregate the various weather measures used in the computation of the ACI. We look at each of the six ACI components (non-standardized) separately for each of the seven regions used in the ACI, leading to a total of 40 series with non-missing data.[21] We then compute the leading principal component from those series and replace ACI with this series in our VAR.[22] Figure A.2 shows that our results are robust to this alternative measure of ACI and are not driven by a specific way of how the ACI is aggregated.

[21] There is no data for the sea level component for the Midwest, and there are missing values in non-standardized data of the T10 component for Alaska.

[22] Consistent with our treatment of the ACI, we seasonally adjust the resulting principal component.

5.3 Excluding T10

To assess possible ambiguities concerning the role of low temperatures (the component T10) in forming the ACI, we now construct an alternative severe weather index that is equal to the original ACI, except that it drops T10 from the computation. Figure A.3 shows that our results are robust to dropping the T10 component.

5.4 Individual Component Analysis

Furthermore, 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). We order this additional variable first in each of those models (keeping the overall ACI variable in our VAR as well) and estimate the impulse response to an unexpected change in this ACI component, using the same recursive identification scheme as in our benchmark. 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. Figure A.4 in the appendix provides the full set of IRFs. We note several observations: (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.

5.5 Non-Gaussian Distribution

We have also estimated a version of our model that assumes that each structural shock follows an independent t-distribution. This has the additional benefit that t-distributed random variables can be reinterpreted as Gaussian random variables multiplied by an iid standard deviation that varies over time (Geweke 1993), hence we can view this as a model with both low-frequency changes in volatility (which our benchmark model already has) and high-frequency changes in volatility.

Figure A.5 plots the impulse responses in that case – they are very similar to our benchmark. We have estimated the degrees of freedom of each t-distributed shock. For each of those degrees of freedom, we use the same prior – a Gamma distribution with mean 3 and standard deviation 1.[23] Since a t-distributed random variable might not have a finite variance, we scale impulse responses so that they have the same initial impact on ACI as in our benchmark. We also estimated a version where we fixed the degrees of freedom a priori to the same value as Brunnermeier et al. (2021b) (which implies a finite variance), and find very similar impulse responses. Results for both versions are shown in Figure A.5. The construction of the likelihood function follows Brunnermeier et al. (2021b). We adjust their likelihood function so that the parameters are now convex combinations of two sets of parameters with the weight being determined by the time index t, as in our benchmark.

[23] All other priors are exactly the same as in our benchmark specification with Gaussian shocks.

5.6 Effects of Seasonal Adjustment

To study the effects of seasonal adjustment on our results, we first regress seasonally adjusted ACI on 12 month dummies to study if there is any meaningful residual seasonality. Figure A.6 shows that our seasonal adjustment removed any systematic seasonal patterns. Even for the slight outlier in December, the overlap with the error bands of the months is substantial.

Second, we rerun our analysis using data that is not seasonally adjusted (both for ACI and our economic variables). Figure A.7 shows that our results are robust to not seasonally adjusting the data.

5.7 Trend

To assess whether or not the clear trend in ACI has an effect on our results, we first detrend ACI using a third-order polynomial and rerun our analysis. As Figure A.8 shows, our results are robust to removing the trend in ACI.

This result is not surprising: the trend in ACI is well captured by the systematic part of the VAR in our original specification with trending ACI. Figure A.9 plots the ACI series as well as the posterior median of the one period ahead expectation of ACI. We see that the upward trend is completely captured by the systematic part of the ACI and hence does not influence estimates of the shock to ACI, which is the crucial object we need to estimate for our identification scheme.

6 Conclusion

We incorporate a novel index of severe weather shocks into a VAR analysis of the US macroeconomy and document that an increase in severe 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 severe weather can cause modest but persistent damages to economic growth and affect price stability even in a developed economy like the U.S.. These findings are relevant, especially as climate change is predicted to increase the frequency or intensity of severe weather (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 workhorse integrated assessment models (e.g., Nordhaus 1993; Golosov et al. 2014; Hassler and Krusell 2018). Our result on the persistent effect of severe weather shocks on aggregate consumption growth can be useful for future research that studies the response of asset prices to weather events in consumption-based asset pricing models (e.g., see the open question of the so-called "climate beta" in Dietz et al. 2018).

A limitation of our project is that currently we do not have clear evidence as to which underlying mechanism is likely to be at play. Potential mechanisms that explain the persistent effects of severe weather shocks include financial frictions that amplify and propagate the direct damage of a shock (Phan and Schwartzman 2021), divestment in durable human or physical capital in disaster-prone areas (Alvarez and Rossi-Hansberg 2021), or psychological factors that permanently alter the preferences of affected individuals (Cameron and Shah 2015). We think that an investigation of these potential mechanisms is an exciting avenue for future research.

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A Appendix

A.1 Data

Actuaries Climate Index Available at https://actuariesclimateindex.org/data/. More detailed documentations can be found here and here.

Macro Variables We use the following data from 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 (link), 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.

A.2 Bayesian Inference and Priors

Priors We use Gaussian priors throughout our analysis. For parts of our prior, we use an empirical Bayes approach, where we estimate a linear VAR with ordinary least squares (OLS) on our entire sample. The priors for the intercept are centered at the point estimate from this linear VAR with a standard deviation of 1. The prior means 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 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). As is common in the Minnesota prior approach, this prior has an empirical Bayes flavor as well because univariate autoregessive specifications are estimated via OLS for each variable in the VAR (Litterman, 1986). The associated point estimates for the forecast error variance are an input to compute the prior variance of the A_ℓ matrices. We estimate AR(12) processes with an intercept to be consistent with our VAR specification in terms of lag length.

Bayesian Inference We use a sequential Monte Carlo (SMC) method to approximate the posterior (Herbst and Schorfheide 2016, 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.

A.3 Omitted Robustness Check Figures

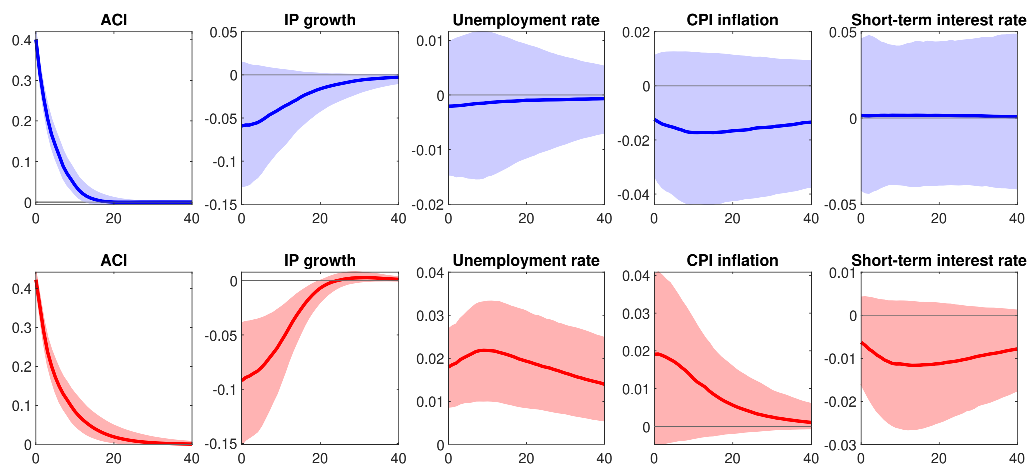


Figure A.1: Results with sample splitting. Top panels: $\tilde{z}_t = 0$ in 1963m4-1990m12; bottom panels: $\tilde{z}_t = 1$ in 1991m1-2019m5. Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

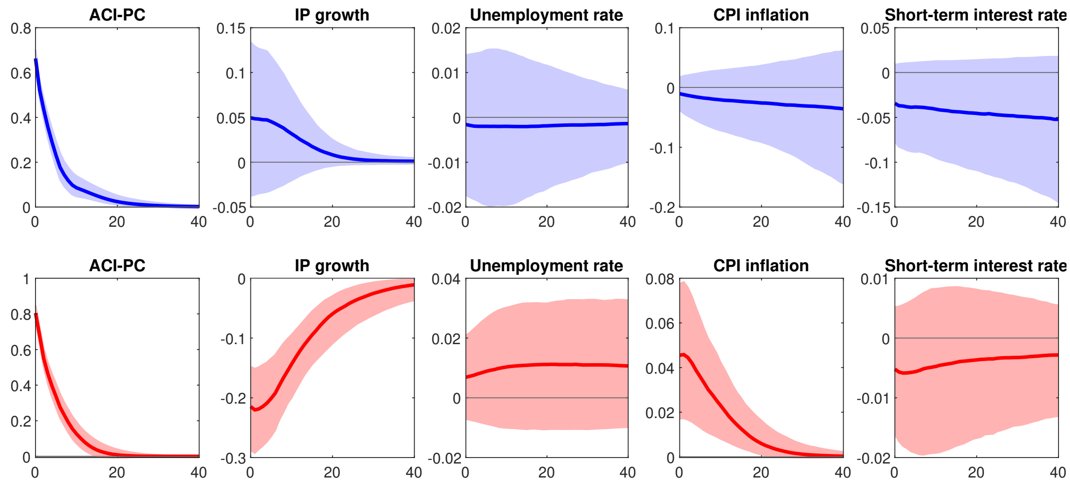
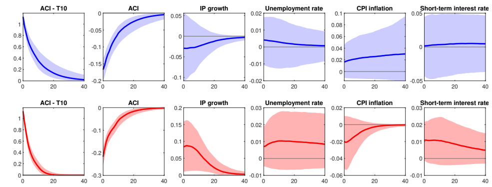


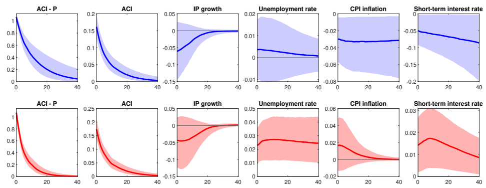
Figure A.2: Impulse responses to a one-standard deviation shock to ACI-PC, which is the first principal component of disaggregated ACI component data. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

Figure A.3: Impulse responses to a one-standard deviation shock to the ACI without $T10$. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

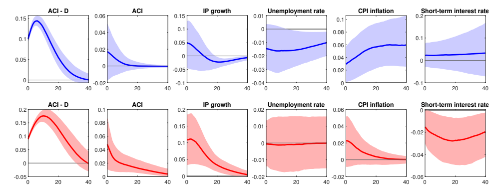
(a) T90



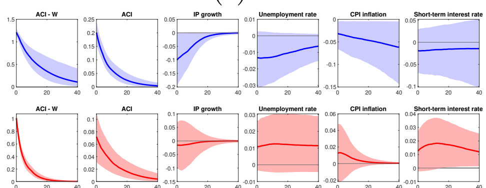
(b) T10



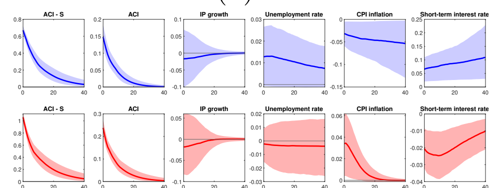
(c) P



(d) D

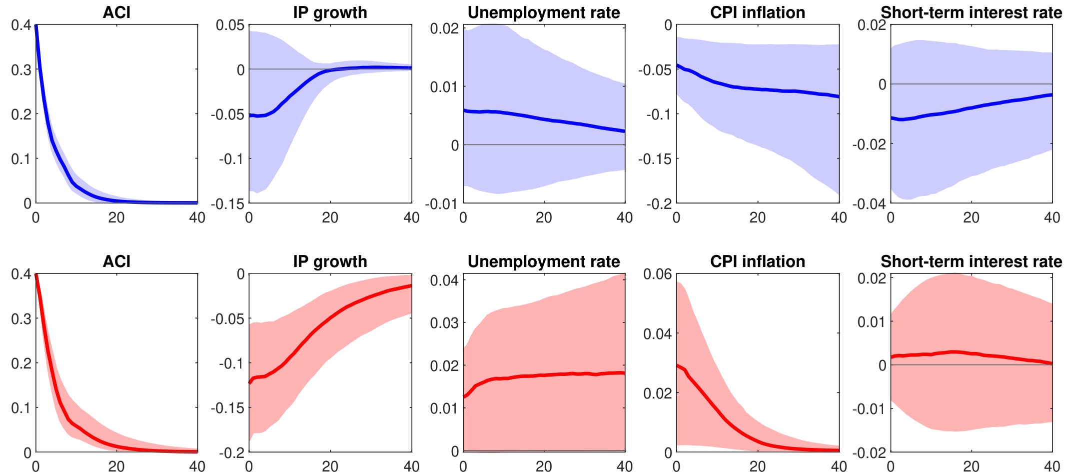


(e) W

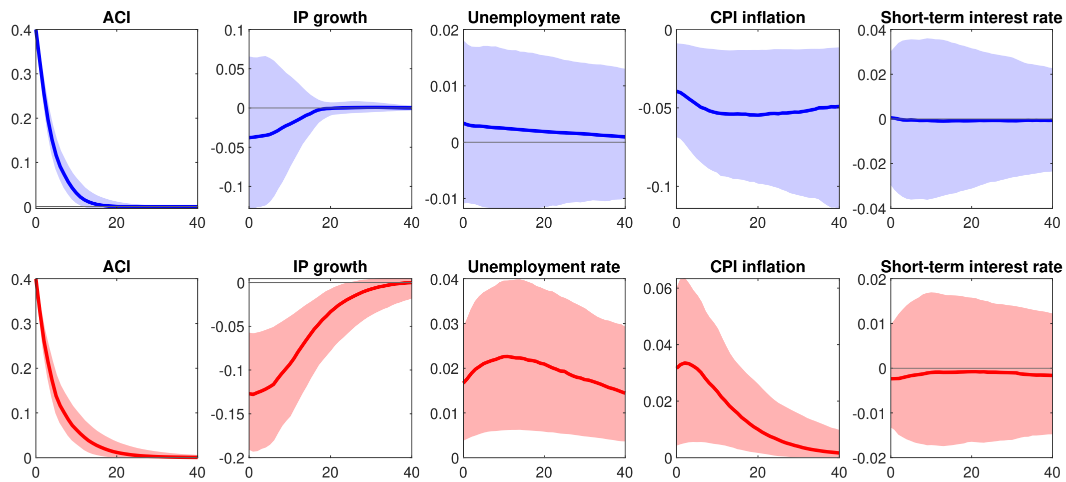


(f) S

Figure A.4: Impulse responses to a one-standard deviation shock to each ACI component. In each of the six panels, we re-estimate our benchmark model in Figure 3, but add one additional component of the ACI at a time; the additional component is ordered first. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.



(a) Version 1: We estimate the degrees of freedom. The priors for each shock's degrees of freedom are a Gamma distribution with a mean of 3 and standard deviation of 1.



(b) Version 2: We fix the degrees of freedom a priori to 5.7.

Figure A.5: Impulse response results assuming independent t-distributed shocks. Otherwise the specification is the same as in Figure 3. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

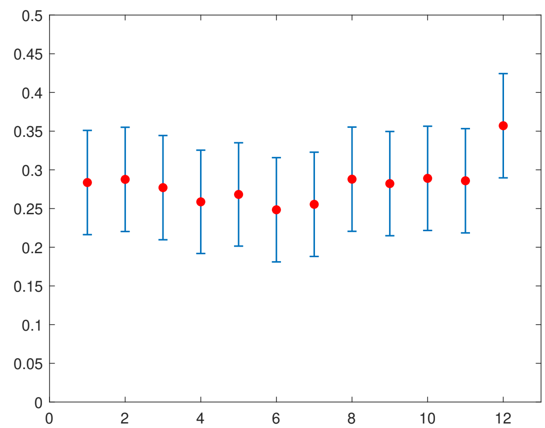


Figure A.6: Regression coefficients of seasonally adjusted ACI on 12 monthly dummies (error bands cover +/- 1 standard deviation).

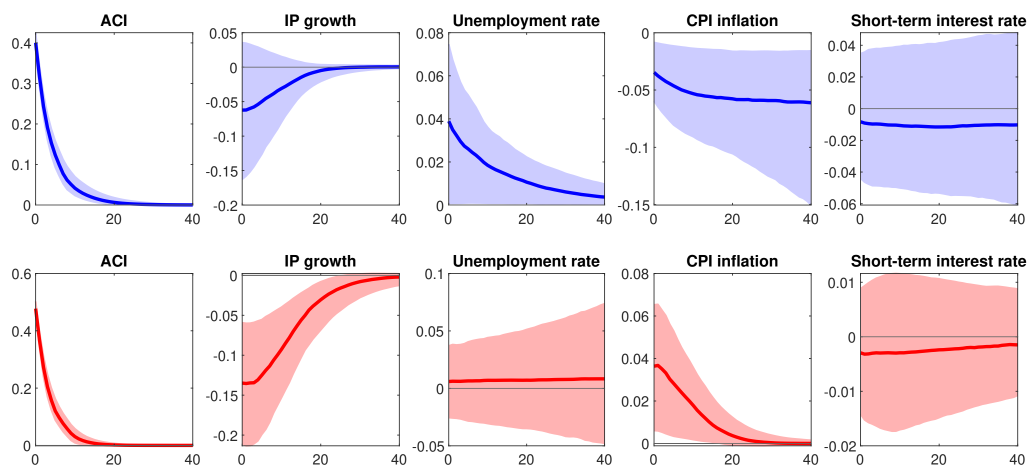


Figure A.7: Impulse response results with nonseasonally adjusted data. Otherwise the specification is the same as in Figure 3. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

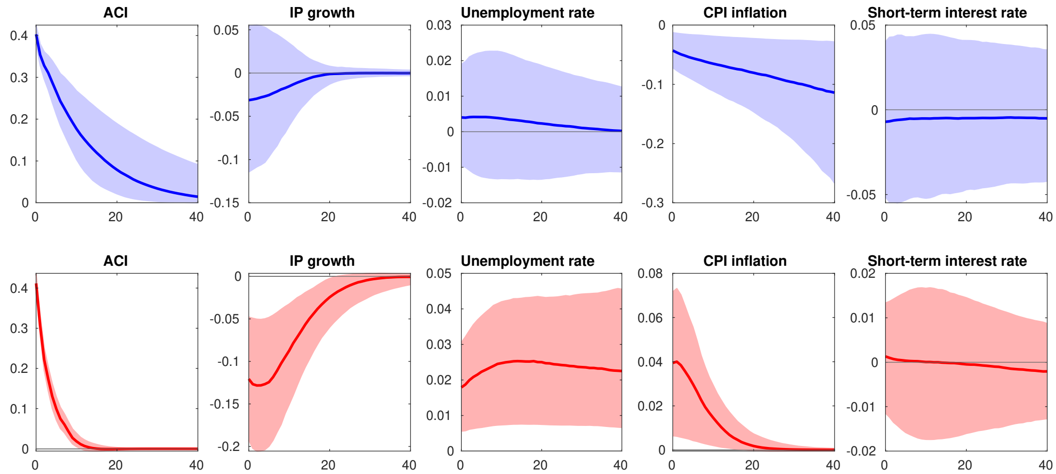


Figure A.8: Impulse responses to a one-standard deviation shock to detrended ACI. Otherwise the specification is the same as in Figure 3. Top panels: beginning of sample ($\tilde{z}_t = 0$); bottom panels: end of sample ($\tilde{z}_t = 1$). Shaded areas represent 68% posterior bands. Horizontal axis: months after the ACI shock.

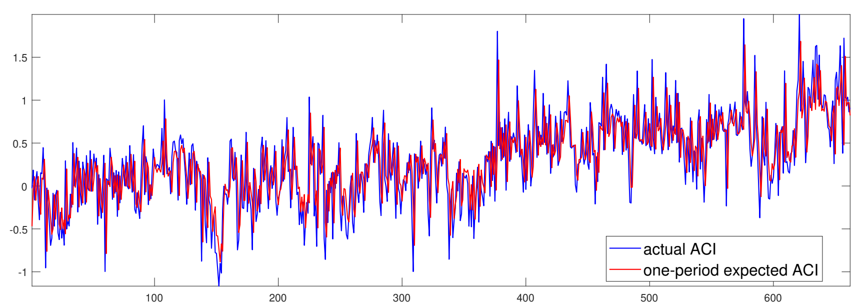


Figure A.9: Actual vs. expected ACI. The blue plots the actual ACI and red line plots the one period ahead expectation of ACI