# Severe Weather and the Macroeconomy

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*The views expressed here are of the authors & should not be interpreted as of the Federal Reserve Bank of Richmond or the Federal Reserve System

## Does severe weather matter for the US Economy?

- The literature so far has focused on either:
    1. developing countries and lower frequencies (Dell, Jones, and Olken 2012; Hsiang and Jina 2014; Bakkensen and Barrage 2018...)
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- **This paper: Direct measures of extreme weather events**
- Have these effects changed over time (evidence of adaptation)?
- **This paper: Use a nonlinear time series model to find that the effects of these shocks, but not their volatility, have become more severe.**

# Data

# Actuaries Climate Index: Components

A monthly index of climate risks, based on a basket of extreme climate events & sea level rise:

1. T90: Frequency of extreme high temperatures
2. T10: Frequency of extreme low temperatures
3. W: Frequency of high winds
4. P: Maximum amount of heavy precipitation
5. D: Longest period of consecutive dry days last 12 months
6. S: Change in sea level

# Actuaries Climate Index: Construction

- Weather data measured on grid with resolution of 2.5 by 2.5 degrees latitude and longitude (except $S$)
- Standardize each component (using location- and month-specific mean and standard deviation) relative to benchmark period (1961-1990)
- Average across all grid points/locations
- $ACI = \text{mean}(T90_{std} - T10_{std} + P_{std} + D_{std} + W_{std} + S_{std})$

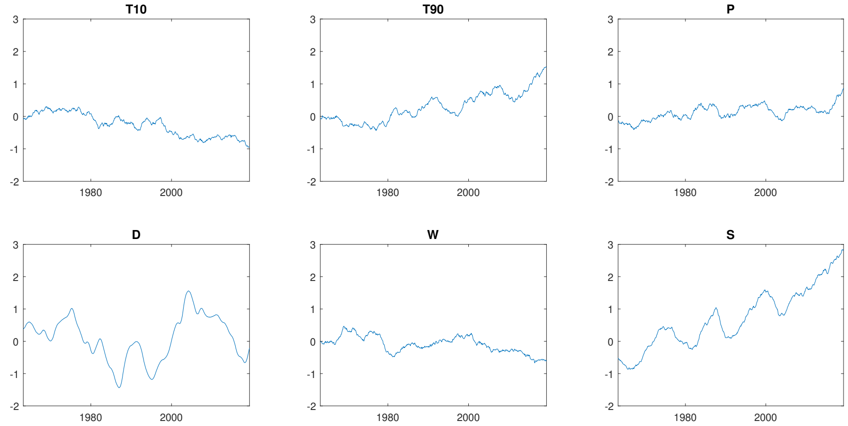



**Figure 1:** The six components of the ACI (low temperatures, high temperatures, heavy precipitation, drought, high wind and sea level) for the continental US.

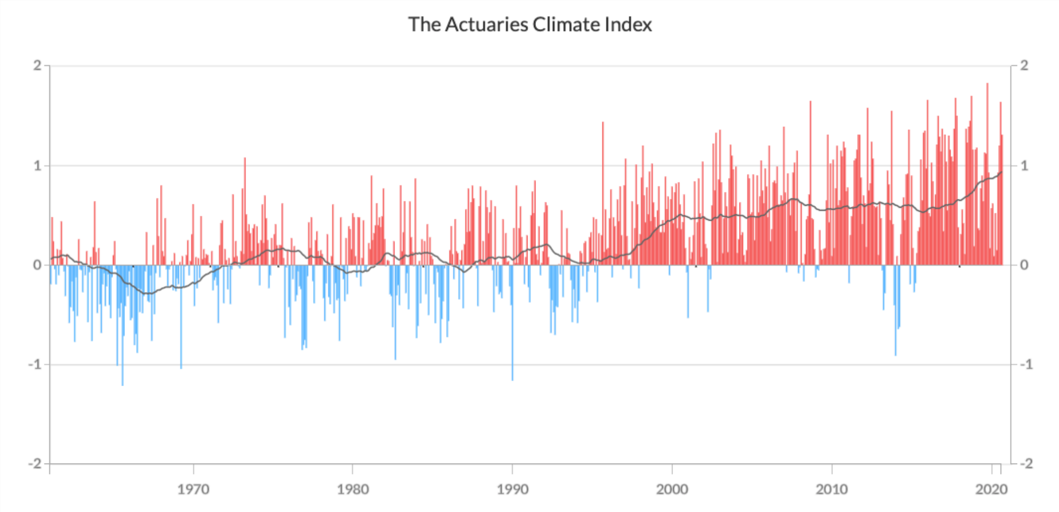

The Actuaries Climate Index
2
1
0
-1
-2
1970
1980
1990
2000
2010
2020

Figure 2

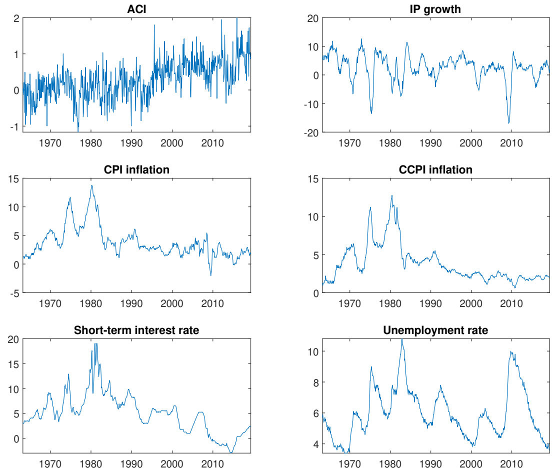



Figure 3: US data (after seasonal adjustment)

# Identification and Econometric Model

# Identification: Some preliminaries

- I'll talk about identification in a linear model first to economize on notation
- **Definition of forecast error:** $\mathbf{u}_t = \mathbf{y}_t - E_{t-1}\mathbf{y}_t$
- **Going from forecast error to structural shocks:** $\mathbf{u}_t = \Sigma \mathbf{e}_t$, $\mathbf{e}_t \sim N(0, I)$
- For what follows next, assume that *ACI* is ordered first in $\mathbf{y}_t$

# Identification (in a linear model for simplicity)

**Assumption (Identification)**

*We assume that all variation in the ACI coming from unexpected changes from one month to the next (i.e. coming from $\mathbf{u}_t$) is due to the ACI shock we want to identify.*

$$\mathbf{u}_t^1 = \Sigma_{11}\mathbf{e}_t^1$$

*This assumption implies that all elements in the first row of $\Sigma$ except for the very first element $\Sigma_{11}$ are equal to zero.*

# Econometric model: How we allow for time variation

- Smooth Transition VAR with $\mathcal{L} = 12$ lags:

$$\mathbf{y}_t = \tilde{z}_{t-1}(\mathbf{m}_1 + \sum_{\ell=1}^{\mathcal{L}} \mathrm{A}_{\ell,1}\mathbf{y}_{t-\ell} + \Sigma_1 \mathbf{e}_t) + (1 - \tilde{z}_{t-1})(\mathbf{m}_2 + \sum_{\ell=1}^{\mathcal{L}} \mathrm{A}_{\ell,2}\mathbf{y}_{t-\ell} + \Sigma_2 \mathbf{e}_t) \qquad (1)$$

- $0 \leq \tilde{z}_{t-1} \leq 1$

- Expectations and Forecast Error:

$$E_{t-1}\mathbf{y}_t = \tilde{z}_{t-1}\left(\mathbf{m}_1 + \sum_{\ell=1}^{\mathcal{L}} \mathrm{A}_{\ell,1}\mathbf{y}_{t-\ell}\right) + (1-\tilde{z}_{t-1})\left(\mathbf{m}_2 + \sum_{\ell=1}^{\mathcal{L}} \mathrm{A}_{\ell,2}\mathbf{y}_{t-\ell}\right) \tag{2}$$

$$\mathbf{u}_t = \left(\tilde{z}_{t-1}\Sigma_1 + (1-\tilde{z}_{t-1})\Sigma_2\right)\mathbf{e}_t \tag{3}$$

- Benchmark: time-transition

$$\tilde{z}_t := \frac{t+1}{T}, \quad \forall 0 \leq t \leq T-1$$

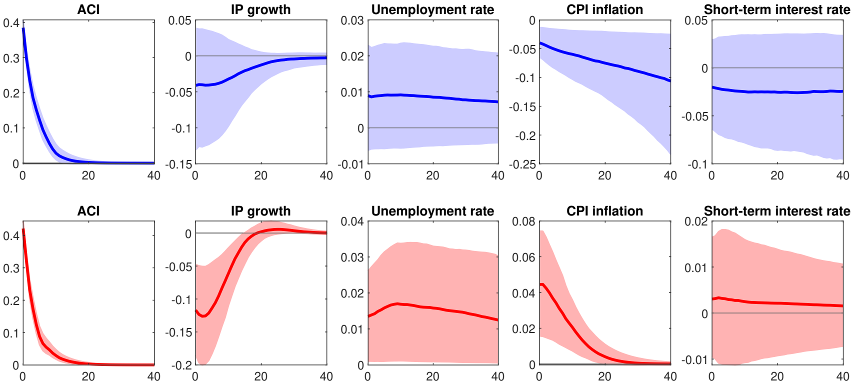
# Why is time variation important?

- Microeconometric studies have tried to tackle time variation by splitting their sample (Barreca, Clay, Deschene, Greenstone, and Shapiro 2016) $\longrightarrow$ nested in our approach
- Allowing for time variation is key to studying **adaptation**

- Bayesian approach
- Approximate posterior via sequential Monte Carlo (SMC) - Herbst & Schorfheide, Bognanni & Herbst
- Standard Minnesota type-priors for $\mathbb{A}$.
- **Priors are the same for both sets of parameters (beginning and end of sample) $\rightarrow$ differences over time driven by likelihood**

# Results

# Impulse responses to ACI shock at beginning & end of sample



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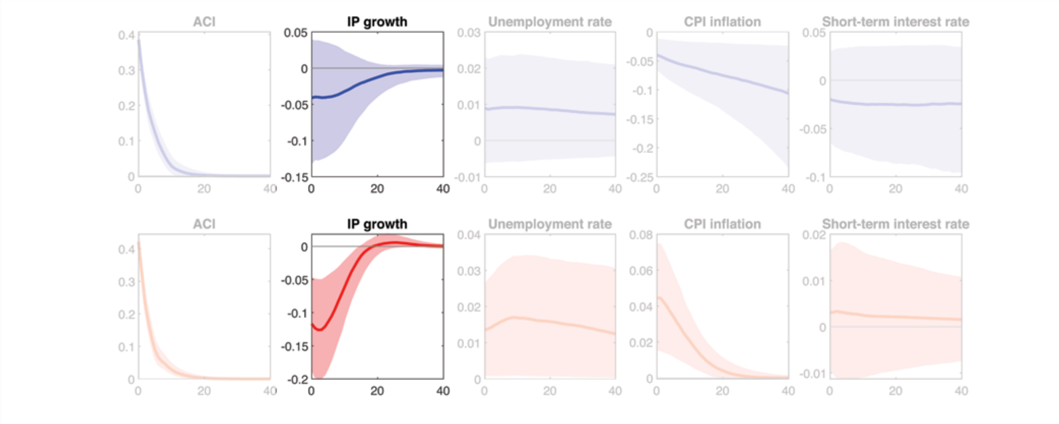

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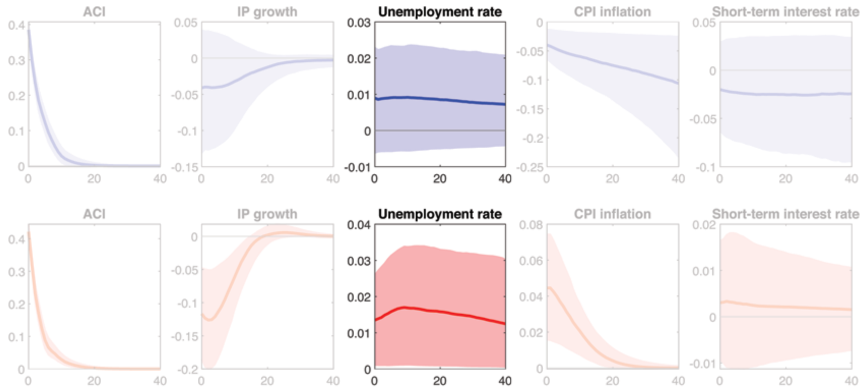

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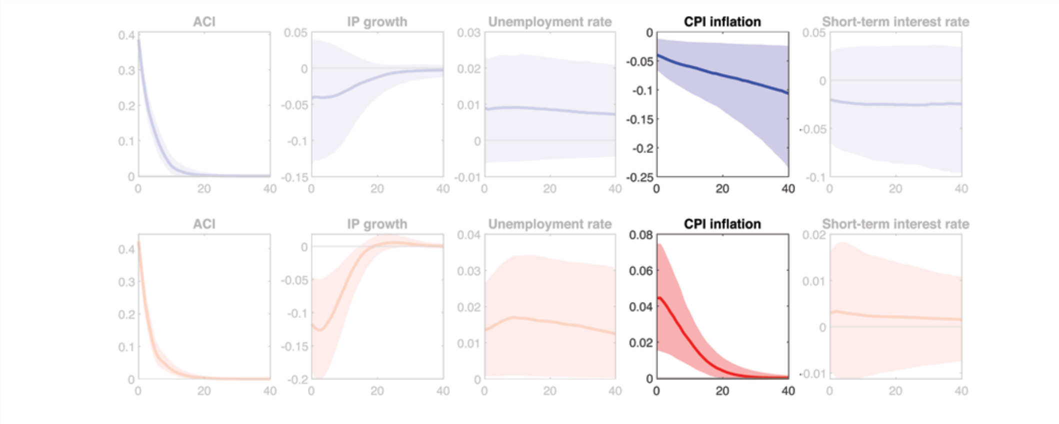
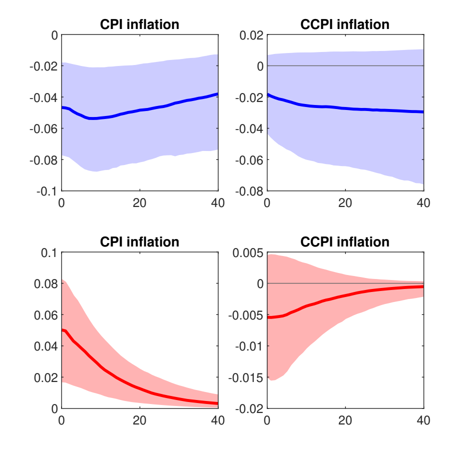


# Impulse responses to ACI shock at beginning & end of sample

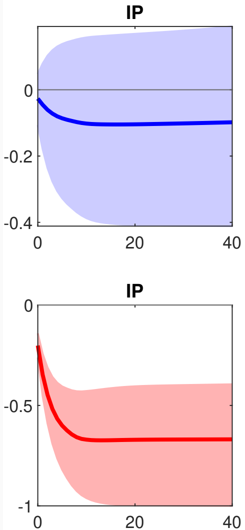
# Digging deeper: Inflation

- Run same specification as before, but add core CPI inflation (y/y) as an additional variable
- Responses of other variables very similar to benchmark



# Digging deeper: Level effect on log IP

- Run same specification as before, but replace y/y IP growth with m/m annualized IP growth - then cumulate those responses.
- Responses of other variables very similar to benchmark
- Reminiscent of Hsiang and Jina's finding of trend of effects of cyclones
- Substantial discussion of trend vs growth rate effects (Dell, Jones, and Olken)
- Useful for calibration of damage function in equilibrium / IA models



# How important are weather shocks?

| | ACI | IP growth | Unemployment rate | CPI inflation | interest rate |
|---|---|---|---|---|---|
| **Beginning of Sample** | | | | | |
| | h=12 | h=12 | h=12 | h=12 | h=12 |
| 16th | 99.97% | 0.03% | 0.03% | 0.21% | 0.01% |
| 50th | 99.99% | 0.30% | 0.39% | 1.52% | 0.15% |
| 84th | 99.99% | 1.16% | 1.66% | 3.96% | 0.66% |
| **End of sample** | | | | | |
| | ACI | IP growth | Unemployment rate | CPI inflation | interest rate |
| | h=12 | h=12 | h=12 | h=12 | h=12 |
| 16th | 100.00% | 0.37% | 0.10% | 0.16% | 0.11% |
| 50th | 100.00% | 1.79% | 0.97% | 1.12% | 1.15% |
| 84th | 100.00% | 4.76% | 3.31% | 3.23% | 4.92% |

**Table 1:** Variance decomposition

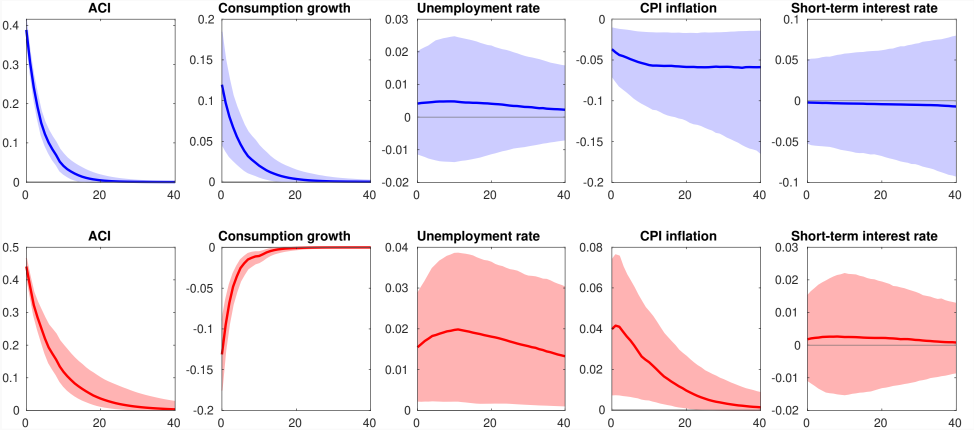
# How important are weather shocks?

| | ACI | IP growth | Unemployment rate | CPI inflation | interest rate |
|---|---|---|---|---|---|
| End of sample | | | | | |
| | h=12 | h=12 | h=12 | h=12 | h=12 |
| **16th** | 100.00% | 0.37% | 0.10% | 0.16% | 0.11% |
| **50th** | 100.00% | 1.79% | 0.97% | 1.12% | 1.15% |
| **84th** | 100.00% | 4.76% | 3.31% | 3.23% | 4.92% |

- Compare to Smets-Wouters: Monetary policy shock at posterior mode explains 10 percent or less of GDP growth and inflation at similar horizons.

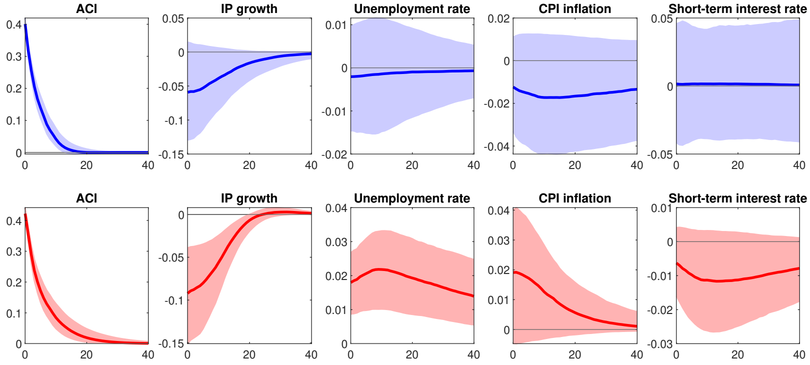
# Further Results

# Consumption Growth



- Robustness checks
  - Splitting the sample: $\tilde{z}_{t-1} = 0$ until 1990, $\tilde{z}_{t-1} = 1$ after Result
  - With non-seasonally adjusted data Result
  - t-distributed errors Result
  - Detrended ACI Result
  - Principal Component Analysis Result
  - Alternative transition variables: lagged MA of ACI & lagged MA of CO2 concentration Results

# Splitting the sample: $\tilde{z}_{t-1} = 0$ until 1990, $\tilde{z}_{t-1} = 1$ after

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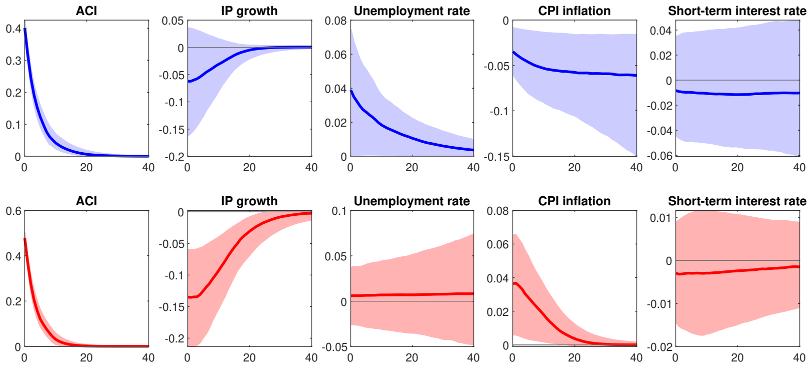
# Non Seasonally Adjusted

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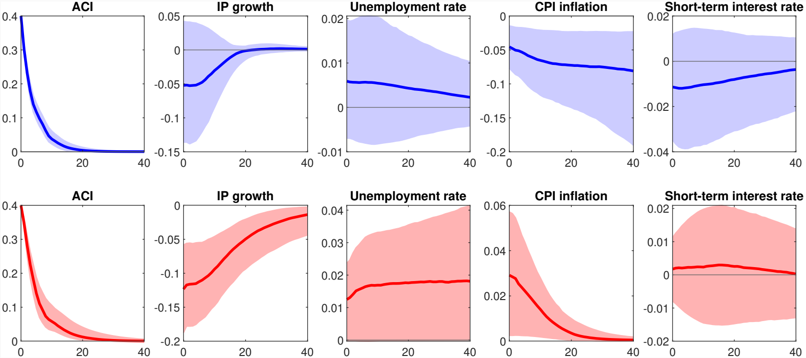
# T-DISTRIBUTED ERRORS

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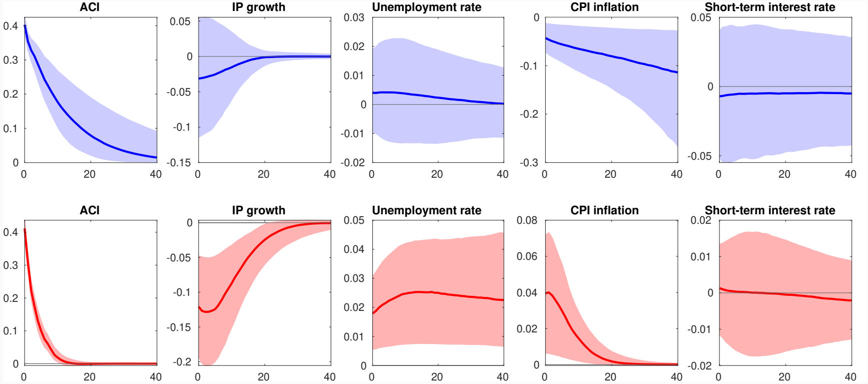

ACI
IP growth
Unemployment rate
CPI inflation
Short-term interest rate
0.4
0.3
0.2
0.1
0
0.05
-0.05
-0.1
-0.15
0.03
0.02
0.01
-0.01
-0.02
-0.2
-0.3
20
40
ACI
IP growth
Unemployment rate
CPI inflation
Short-term interest rate
0.04
0.08
0.06


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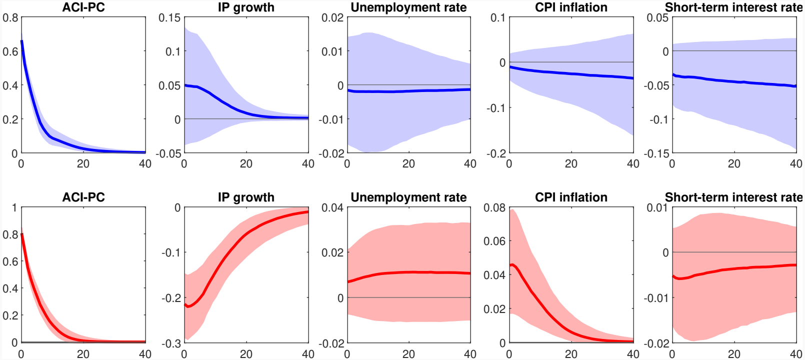
# Principal Component Analysis w/ disaggregate components

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# Individual ACI components

- **What drives our results?**
  - Adding one ACI component at a time to our STVAR
  - Precipitation has no effect on IP growth either at beginning or end of the sample, but does increase unemployment at end of the sample Result
  - The decrease in IP growth at end of the sample is driven by changes in both high and low temperatures Result
  - Sea level changes lead to changes in inflation consistent with those we see in our benchmark results Result

# Precipitation Shock


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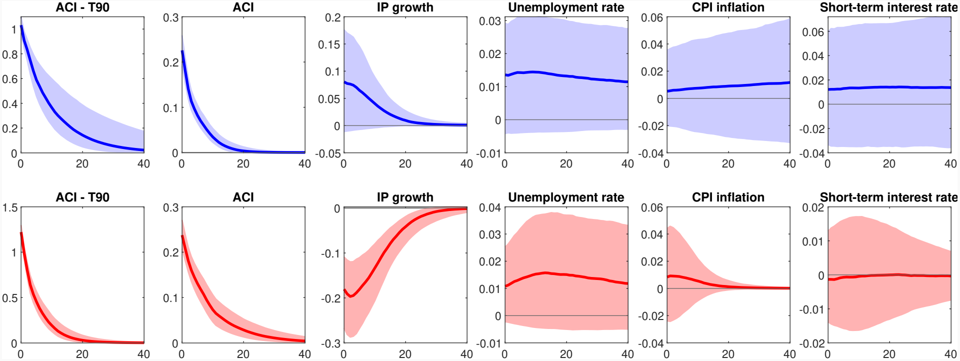
# High Temperature Shock

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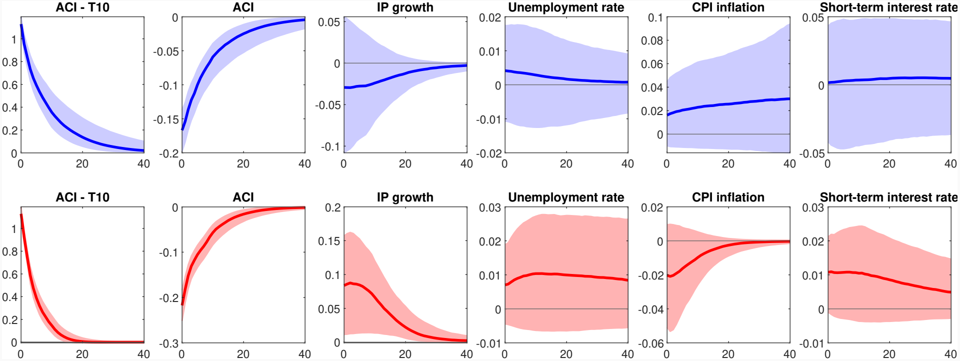
# Low Temperature Shock

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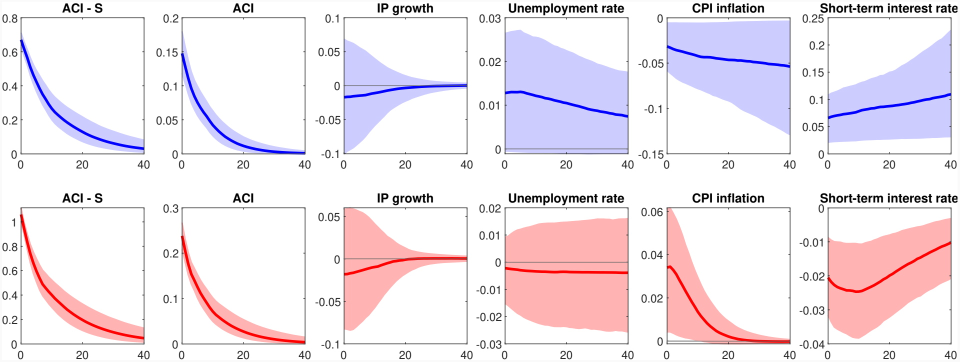
# Sea Level Shock

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# Conclusions

- Substantial changes in the effects of extreme weather events over the last decades
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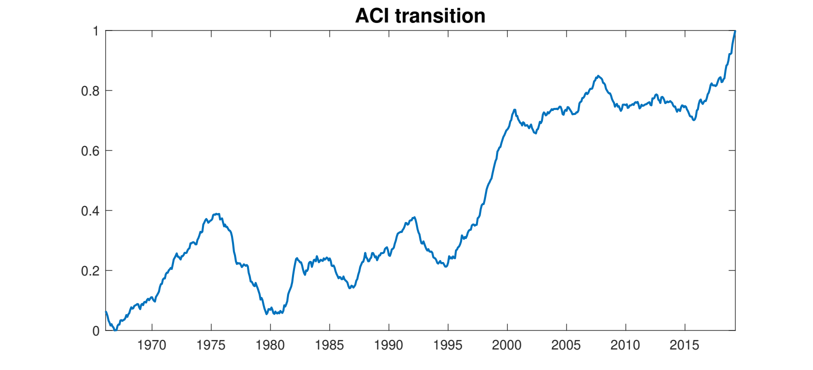
- Working hypothesis: lack of adaptation
- The road ahead: effects on different sectors, different regions

# Alternative transition: Lagged MA of ACI

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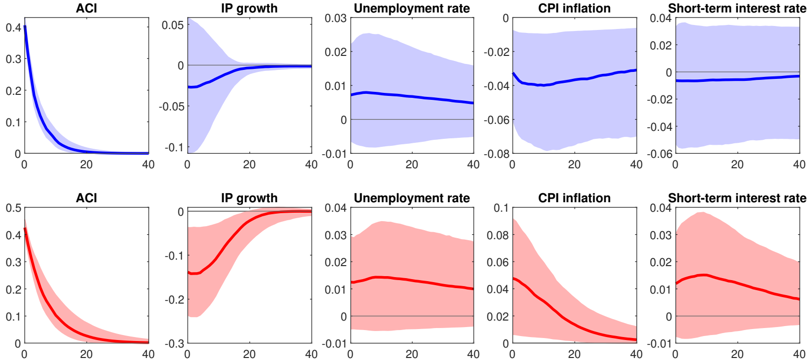
# Responses to ACI shock: Lagged MA of ACI as transition variable

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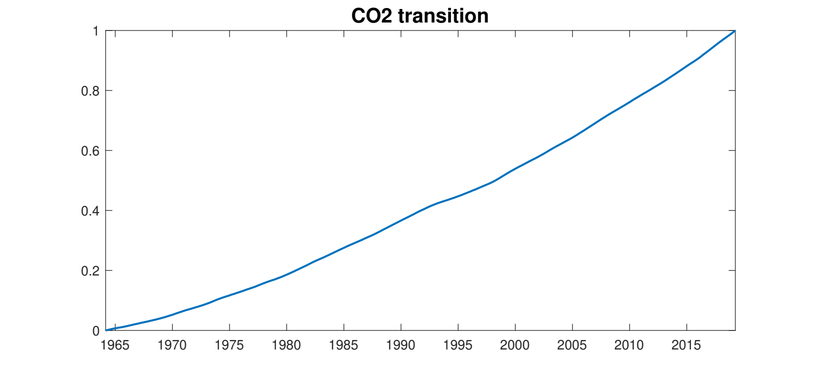
# Alternative transition: Lagged MA of CO2 Concentration

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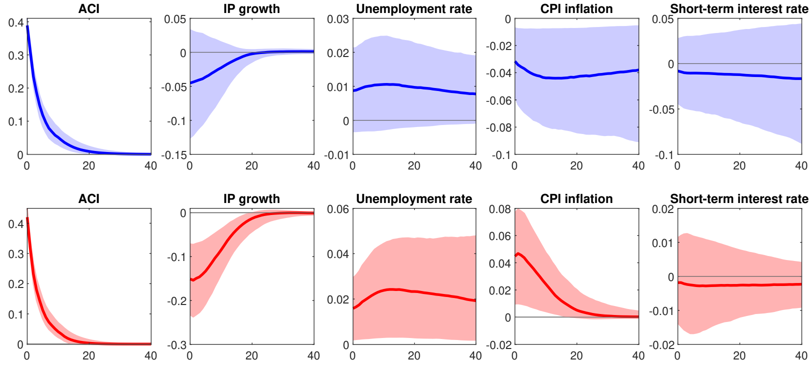


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