

The role of heterogeneity and production networks in the economic impact of weather shocks

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Motivation I

- Higher heterogeneity and volatility in weather due to global warming.
 - Economic impact of local fluctuations
- Weather and climate affect **heterogeneously** regions and sectors
 - Improve the allocation of federal resources
 - Possible bias due to a **compositional effect**
- Economic activity is **connected** across regions and sectors
 - Firms are also exposed to weather shocks from other regions
 - Underestimation of weather effects due to no inclusion of indirect exposure

Motivation II

- I study the economic implications of state and sector specific sensitivity to weather fluctuations and interregional production networks in the United States
- Literature mostly focuses on the long-run effects
 - Less is known about the short-run, I fill this gap.
 - Policy interventions differ between long and short-run

This paper:

- 1. Builds a multi-region multi-sector GE equilibrium model**
 - Heterogeneous sensitivities to weather shocks across regions and sectors.
 - Sectors are exposed to weather from other regions via production networks.
 - Motivates an econometric analysis and provides an aggregation rule
- 2. Explores the local impact of weather shocks on real production**
 - Data on state-sector GDP, weather anomalies, and interregional trade
 - Nonlinear panel regressions with state and sector specific slopes.
- 3. Calculates the aggregate elasticity of weather shocks**
 - Aggregation rule from the GE model + estimated local impacts.

Preview of results:

1. Impact of weather anomalies at state level

- Local impact is non-linear and heterogeneous across states and sectors
- Differences across states are mostly due to state-specific conditions rather than sectoral composition.
- Exposure to weather shock through networks amplifies the effect of weather shocks

2. Aggregate effect of weather anomalies on economic activity

- Models that do not consider either heterogeneity or networks underestimate the negative impact of weather shocks by a factor of 3.
- Between these two channels, networks appears as more important
- An increase in temperatures by 1 Celsius degree would contract the economy by 1.14 percent when both mechanisms are active

Contribution to the literature

- **Econometric estimates of the economic impact of climate change and weather:** Hsiang [2010], Dell et al. [2012], Dell et al. [2014], Deryugina and Hsiang [2014], Burke et al. [2015], Colacito et al. [2018], Acevedo et al. [2020], Hsiang [2016]
My paper: Exploits jointly geographical and sectoral variation in a econometric setup.
- **Climate Change in General Equilibrium Frameworks:** Donadelli et al. [2017], Galic and Vermandel [2020], Rudik et al. [2022], Leduc and Wilson [2023], Bilal and Rossi-Hansberg [2023].
My paper: Focuses the analysis in the short-run
- **Sectoral interlinkages:** Acemoglu et al. [2012], Carvalho and Nechoi [2016], Barrot [2016], Caliendo et al. [2018].

Outline of the talk

1. The model with state and sector specific sensitivity
2. The model with heterogeneity and production networks
3. Macroeconomic implications of heterogeneity and network linkages

A model with state and sector specific sensitivity

- N regions, each one with $J + 1$ sectors.
- Each sector produces intermediate goods using only labor

$$y_n^j = z_n^j(\tilde{\tau}_n) \left(l_n^j\right)^{\alpha_n}$$

where $\tilde{\tau}$ denote weather-fluctuations

- The final output for region n is:

$$Y_n = \prod_j \left(y_n^j\right)^{b_n^j} \quad \sum_j b_n^j = 1$$

- A representative household with preferences.

$$U = \prod_n c_n^{\beta_n} \quad \sum_n \beta_n = 1$$

- Labor is supplied inelastically and can be moved freely across regions

Equilibrium conditions

- At equilibrium, weather affects production through productivity

$$d \ln y_n^j = d \ln z_n^j(\tilde{\tau}) = f_n^j(\tilde{\tau}_n)$$

- Fluctuations in aggregate production:

$$d \ln Y = \sum_{n,j} \beta_n b_n^j d \ln y_n^j \quad (1)$$

- β_n and b_n^j can be inferred as shares in nominal GDP

$$\beta_n = \frac{p_n y_n}{PY}; \quad b_n^j = \frac{p_n^j y_n^j}{p_n Y_n}$$

Suppose a second-order approximation around no-weather shocks:

$$f_n^j(\tilde{\tau}) \approx \theta_{n1}^j \tilde{\tau}_n + \theta_{n2}^j \tilde{\tau}_n^2$$

where

$$\theta_n^j = \underbrace{\theta_n}_{\text{regional specific}} + \overbrace{\theta_j}^{\text{sector specific}} + \tilde{\theta}_n^j$$

if $\mathbb{E}[\tilde{\theta}_n^j] = 0 \forall n, j$, then I have

$$d \ln y_n^j \approx (\theta_{n1} + \theta_{j1}) \tilde{\tau}_n + (\theta_{n2} + \theta_{j2}) \tilde{\tau}_n^2 + \epsilon_{nj} \quad \text{with } \mathbb{E}[\epsilon_{nj}] = 0 \quad (2)$$

Empirical implementation

The empirical implementation of Equation 2 is:

$$\Delta y_{j,n,t} = \alpha + \rho_j \Delta y_{j,n,t-1} + (\theta_{n,1} + \theta_{j,1}) \tilde{\tau}_{n,t} + (\theta_{n,2} + \theta_{j,2}) \tilde{\tau}_{n,t}^2 + \gamma_j + \gamma_n + \gamma_t + \epsilon_{j,n,t} \quad (3)$$

where :

- Δy_{jnt} : is the log-diff. of the Gross State Product per capita of sector j from state n at year t
- $\tilde{\tau}_{nt}$ is a measure of weather fluctuations
- $\gamma_j, \gamma_n, \gamma_t$ are fixed effects by sector, state, and year.
- ρ_j includes some dynamics.
- θ_n and θ_j are state-specific and sector-specific slopes, respectively.

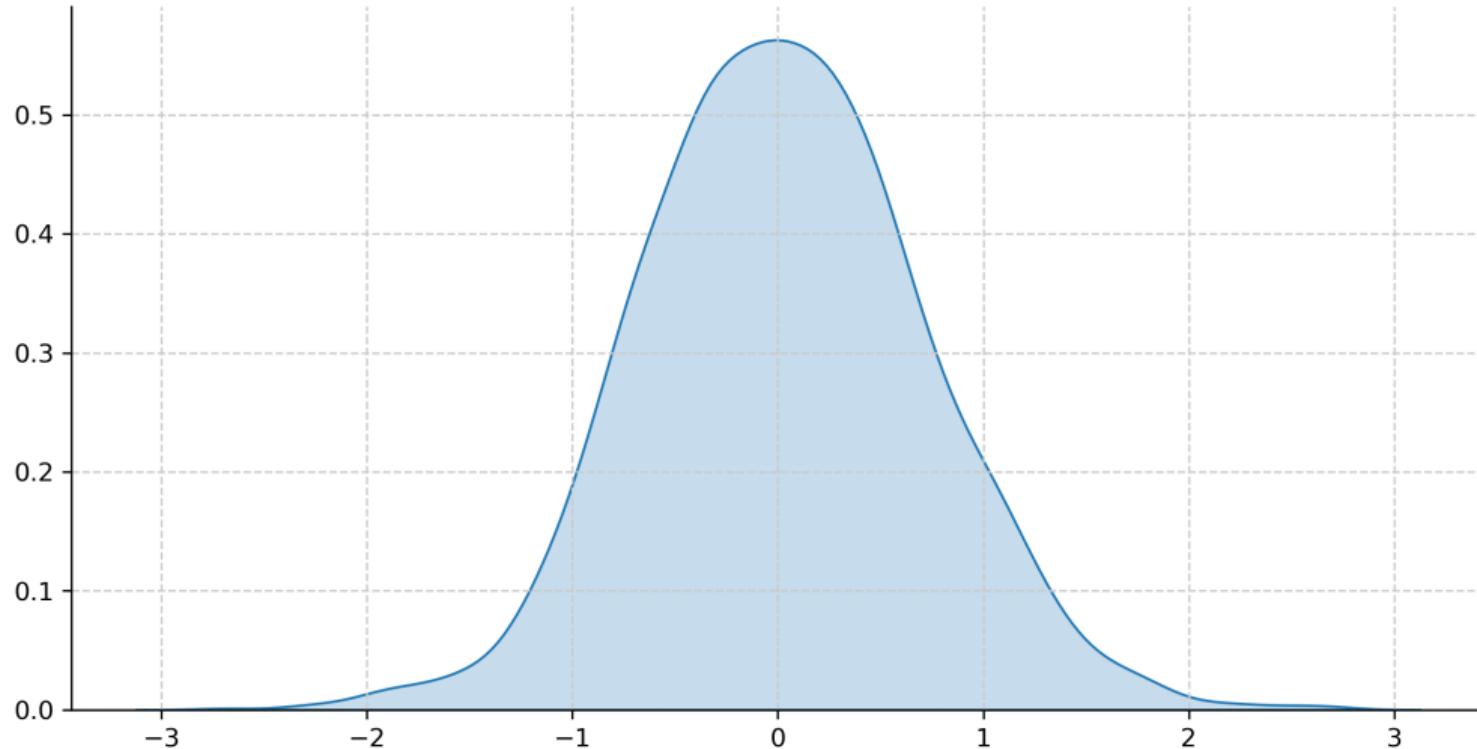
Data:

- Gross State Product per-capita:
 - Annual data for 59 sectors and 48 states from 1970 to 2019.
 - Deflated by Metropolitan or Regional CPI (which is closer)
- Weather fluctuations ($\tilde{\tau}_{n,t}$):
 - Temperature deviations with respect to a 10-year moving average.

$$\tilde{\tau}_{n,t} = \tau_{n,t} - \frac{1}{10} \sum_{h=1}^{10} \tau_{n,t-h}$$

- Exogeneity assumption holds due to using anomalies instead of levels

Distribution of temperatures anomalies



Contemporaneous impact of $\tilde{\tau}$ (per Celsius degree)

- Impact of a weather fluctuation $\tilde{\tau}^o$ -per Celsius degree- on sector j at state n is:

$$\mathcal{G}_{jn}(\tilde{\tau}_{n,t}^o) = \hat{\theta}_{n1} + \hat{\theta}_{j1} + (\hat{\theta}_{n2} + \hat{\theta}_{j2})\tilde{\tau}_{n,t}^o \quad (4)$$

- Two scenarios: (i) $\tilde{\tau}_{small} = 0.5\sigma_{\tilde{\tau}} \approx 0.3C$, (ii) $\tilde{\tau}_{large} = 1.5\sigma_{\tilde{\tau}} \approx 1C$
- We can aggregate \mathcal{G}_{jn} using shares to nominal GDP as weights (equation 1)

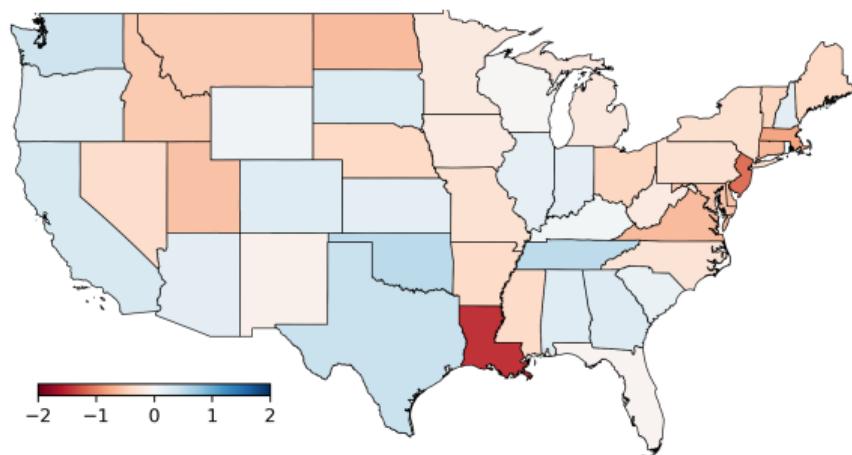
State level: $\mathcal{G}_n(\tilde{\tau}_{n,t}^o) = \sum_j w_{jn} \mathcal{G}_{jn}(\tilde{\tau}_{n,t}^o), \quad w_{jn} = \frac{1}{T} \sum_t \left(\frac{\text{nom GSP}_{jn}}{\sum_j \text{nom GSP}_{jn}} \right)_t$

w_{jn} is the empirical counterpart of b_n^j

Contemporaneous impact of $\tilde{\tau}$ at state level

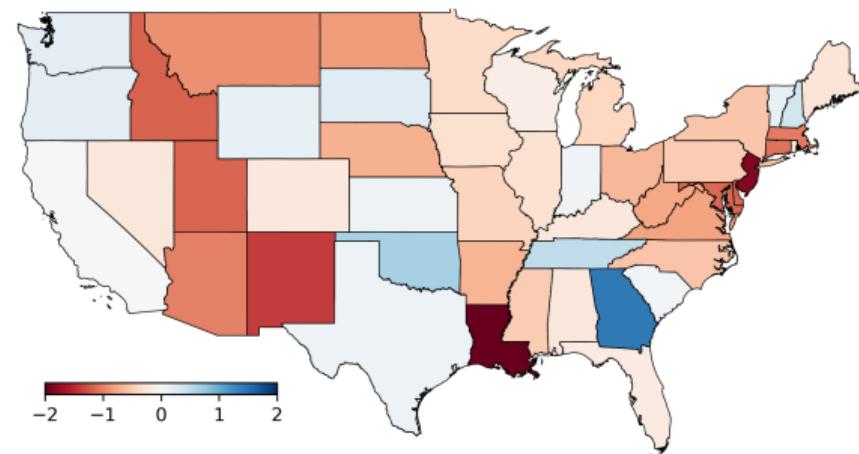
confidence

(a) Small weather shock



Industry level

(b) Large weather shock



Decomposing \mathcal{G}_n

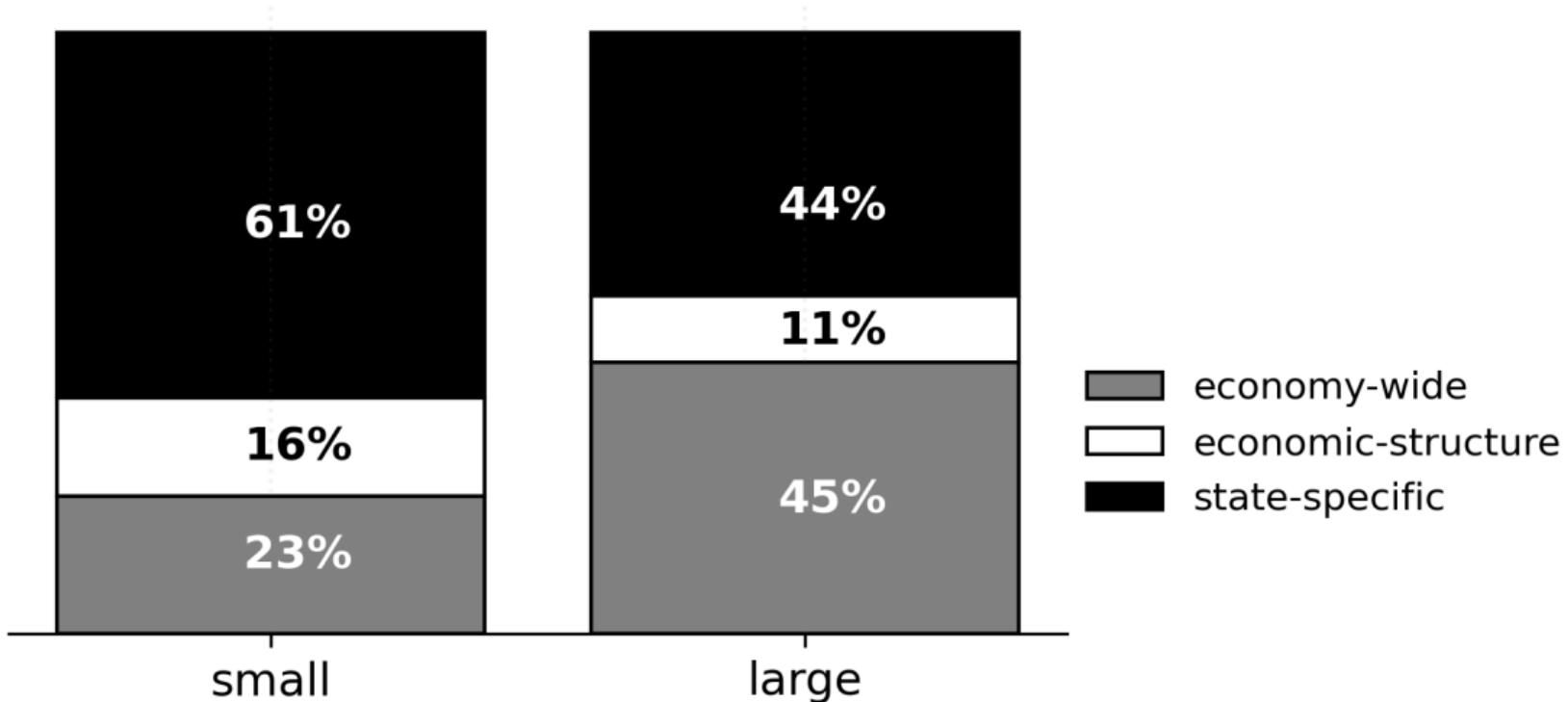
- How much of the differences across states are due to sectoral composition?
- We can decompose the state-level result \mathcal{G}_n in:

$$\mathcal{G}_n = \underbrace{\sum_j \bar{w}_j \mathcal{G}_j}_{\text{economy-wide effect}} + \overbrace{\sum_j \tilde{w}_{jn} \mathcal{G}_j}^{\text{dev. due to economic struct.}} + \underbrace{\sum_j w_{jn} \tilde{\mathcal{G}}_{jn}}_{\Delta \text{ due to region-specific conditions}}$$

where $\bar{w}_j = \frac{1}{T} \sum_t \left(\frac{\text{nom. } GDP_{jt}}{\text{nom. } GDP_t} \right)_t$, $\tilde{w}_{jn} = w_{jn} - \bar{w}_j$, and $\tilde{\mathcal{G}}_{jn} = \mathcal{G}_{jn} - \mathcal{G}_j$

Decomposing \mathcal{G}_n : Average shares

[details](#)



The model with heterogeneity and production networks

- n and m index states and j and i index sector.
- Now, sectors can use final goods as inputs (still CRS)

$$q_n^j = z_n^j(\tilde{\tau}_n) \left(l_n^j\right)^{\tilde{\alpha}_n^j} \prod_m \left(x_{nm}^j\right)^{a_{nm}^j} \quad (5)$$

q_n^j is the gross-output of sector j at state n

- Gross output of the state is:

$$Q_n = \sum_j (q_n^j)^{b_n^j} \quad \sum_j b_n^j = 1 \quad \forall n$$

- Market clearing condition

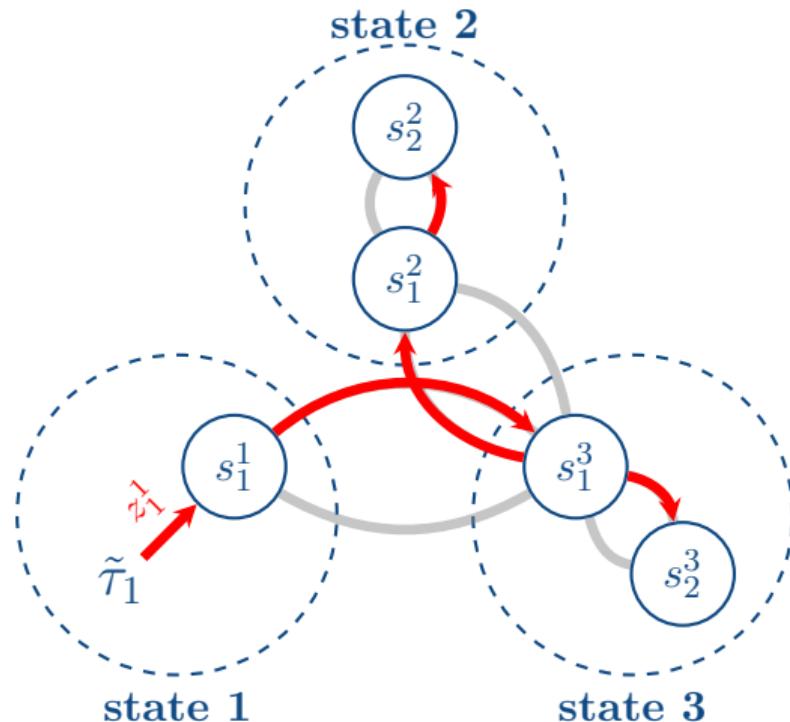
$$q_n = c_n + \sum_{m,j} x_{mn}^j \quad \forall n$$

- The solution of this model implies:

$$d \ln y_n^j = d \ln z_n^j(\tilde{\tau}_n) + \sum_{m,i} \underbrace{a_{nm}^j b_m^i}_{\substack{\text{elements of} \\ \text{IO matrix} \rightarrow A}} d \ln y_m^i$$

where $y_n^j = \frac{wl_n^j}{p_n^j}$ is the real value-added of the sector j in state n

Transmission of a state-specific weather shock



- The cascade of events is summarized by the Leontief-inverse matrix

$$\Psi = (I - A)^{-1} \rightarrow \Psi = I + A + A^2 + A^3 + \dots$$

- Then:

$$d \ln y_n^j = \underbrace{d \ln z_n^j(\tau_n)}_{\text{direct exposure}} + \overbrace{\sum_{i,m} (\psi_{nm}^{ji} - \mathbf{1}_{n=m, j=i}) d \ln z_m^i(\tau_m)}^{\text{exposure through networks}} \quad (6)$$

- Aggregation rule

$$d \ln Y = \sum_{n,j} \beta_n b_n^j d \ln y_n^j \quad \text{where } \beta_n = \frac{p_n c_n}{P C} ; \quad b_n^j = \frac{p_n^j q_n^j}{p_n Q_n} \quad \forall n, j \quad (7)$$

Data for calibration of A

- **USE table:**
 - Transactions between the sectors of the economy at an aggregate level
 - It allows constructing an input-output matrix at the aggregate level
- **Commodity Flow Survey:**
 - Data on shipments across states for 24 tradable sectors
 - How much of a good i , a state m sold to state n
 - I construct the share of state m in the expenditures of state n on good i

details

Empirical Implementation

I run the following regression:

$$\Delta \tilde{y}_{j,n,t} = \alpha + \rho_j \Delta \tilde{y}_{j,n,t-1} + (\theta_{n,1} + \theta_{j,1}) \tilde{\tau}_{n,t} + (\theta_{n,2} + \theta_{j,2}) \tilde{\tau}_{n,t}^2 + \zeta_{n,1} \tilde{\tau}_{jnt}^{network} + \zeta_{n,2} (\tilde{\tau}_{jnt}^{network})^2 + \gamma_j + \gamma_n + \gamma_t + \epsilon_{j,n,t} \quad (8)$$

- $\tilde{\tau}_{jnt}^{network} = \sum_{i,m} (\psi_{jn,im} - \mathbf{1}_{jn=im}) \tilde{\tau}_{mt}$
 - indirect weather shock through the network connections
- I allow $\tilde{\tau}_{jnt}^{network}$ to have a nonlinear effects.
- $\zeta_{n,1}, \zeta_{n,2}$ are state specific

- **Scenario:** every state receives the same weather fluctuation simultaneously
- Impact per Celsius degree:

$$\mathcal{G}_{jn}^{network}(\tilde{\tau}^o) = \overbrace{(\hat{\theta}_{n,1} + \hat{\theta}_{j,1}) + (\hat{\theta}_{n,2} + \hat{\theta}_{j,2})\tilde{\tau}^o}^{\text{direct exposure}} + \underbrace{\frac{\hat{\zeta}_{1n}\tilde{\tau}_{jn}^{net,o}}{\tilde{\tau}^o} + \frac{\hat{\zeta}_{2n}(\tilde{\tau}_{jn}^{net,o})^2}{\tilde{\tau}^o}}_{\text{indirect exposure}}$$

where $\tilde{\tau}_{jn}^{net,o}$ is the value of $\tilde{\tau}_{jn}^{network}$ conditional on $\tilde{\tau}_n = \tilde{\tau}^o \forall n$

- Aggregation at the state level:

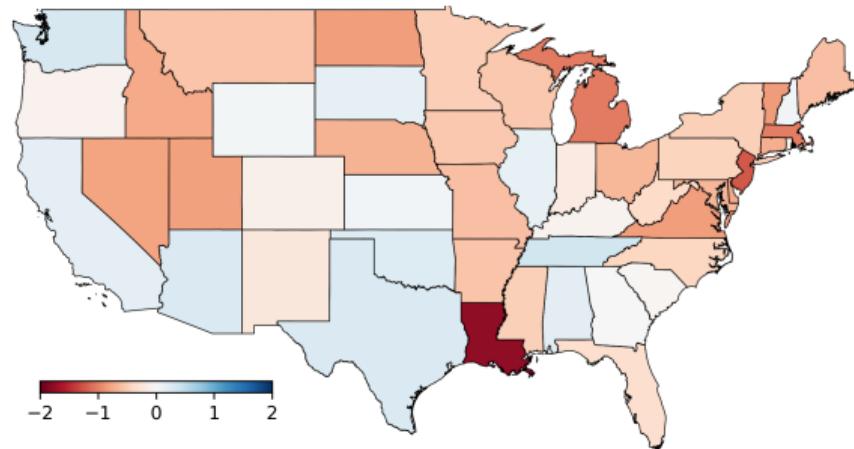
$$\mathcal{G}_n(\tilde{\tau}_{n,t}^o) = \sum_j w_{jn} \mathcal{G}_{jn}(\tilde{\tau}_{n,t}^o)$$

no data about gross output at sector-state level.

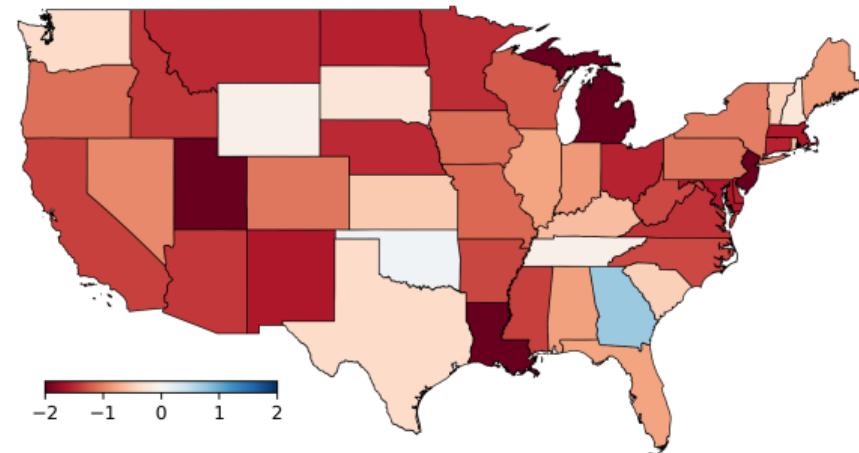
Impact of $\tilde{\tau}$ by state

confidence

(a) Small weather shock



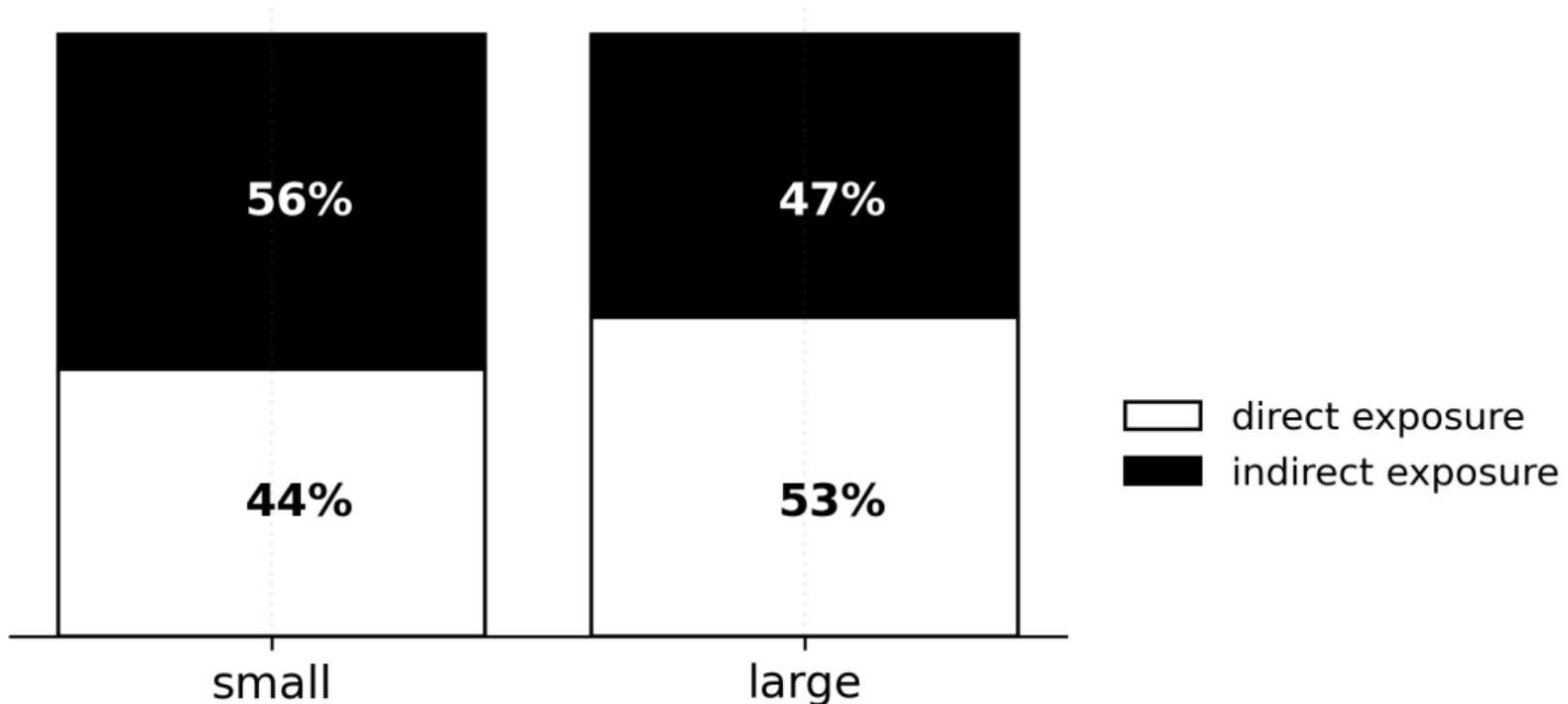
(b) Large weather shock



sectoral results

Direct vs Indirect exposure: Average shares

details



Macroeconomic implications of heterogeneity and network linkages

1. Model with specific sensitivities

$$\sum_n w_n \mathcal{G}_n(\tilde{\tau}^o) \tilde{\tau}^o$$

2. Model with specific sensitivities and

$$\sum_n w_n \mathcal{G}_n^{\text{network}}(\tilde{\tau}^o) \tilde{\tau}^o$$

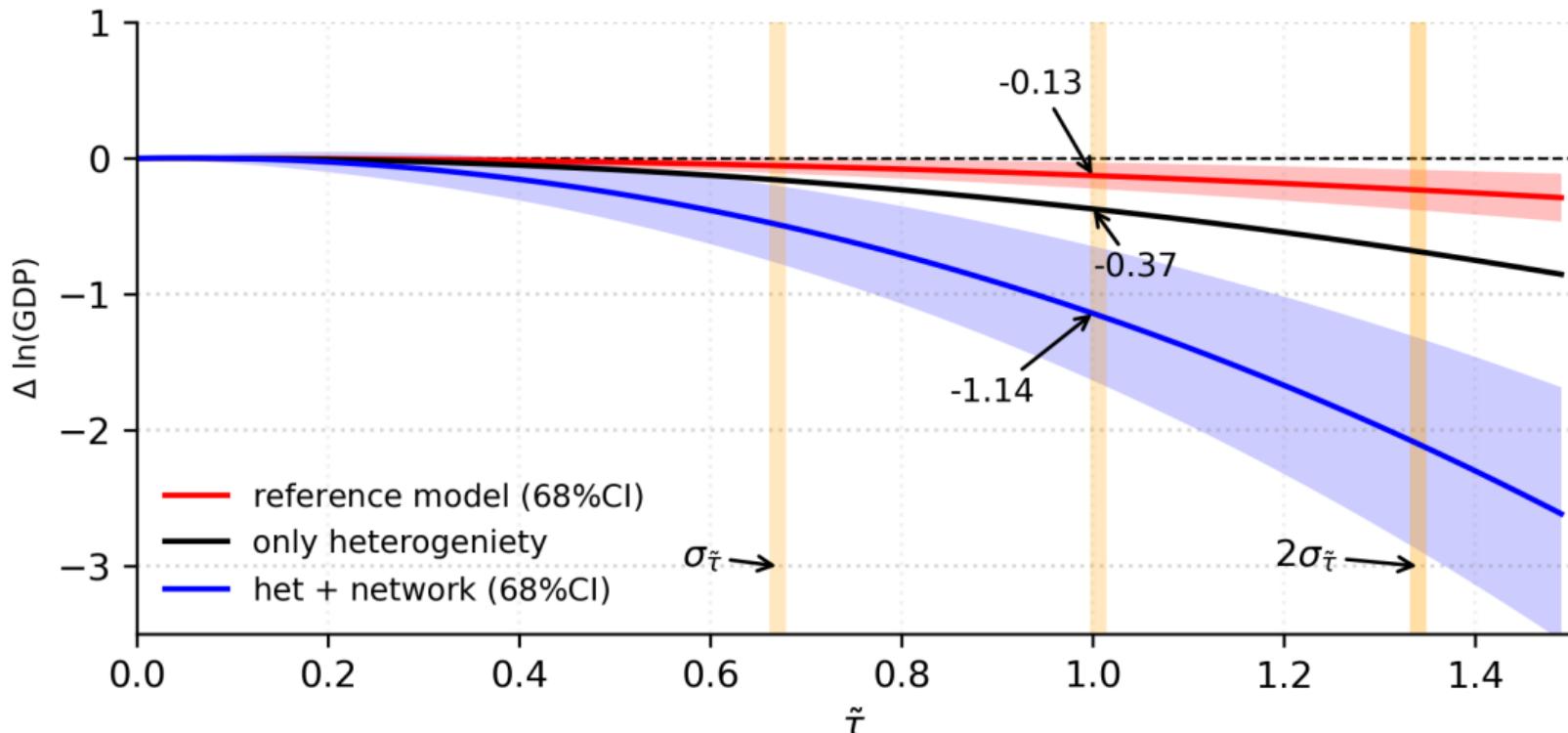
$w_n = \frac{GDP_n}{\sum_n GDP_n}$ is the share of state n to nominal GDP

3. Reference model for comparison:

$$\Delta \tilde{y}_{jnt} = \alpha + \rho \Delta \tilde{y}_{jnt-1} + \varphi_1 \tilde{\tau}_{nt} + \varphi_2 \tilde{\tau}_{nt}^2 + \gamma_j + \gamma_n + \gamma_t + \epsilon_{jnt}$$

Aggregate impact of an weather fluctuations $\tilde{\tau}$

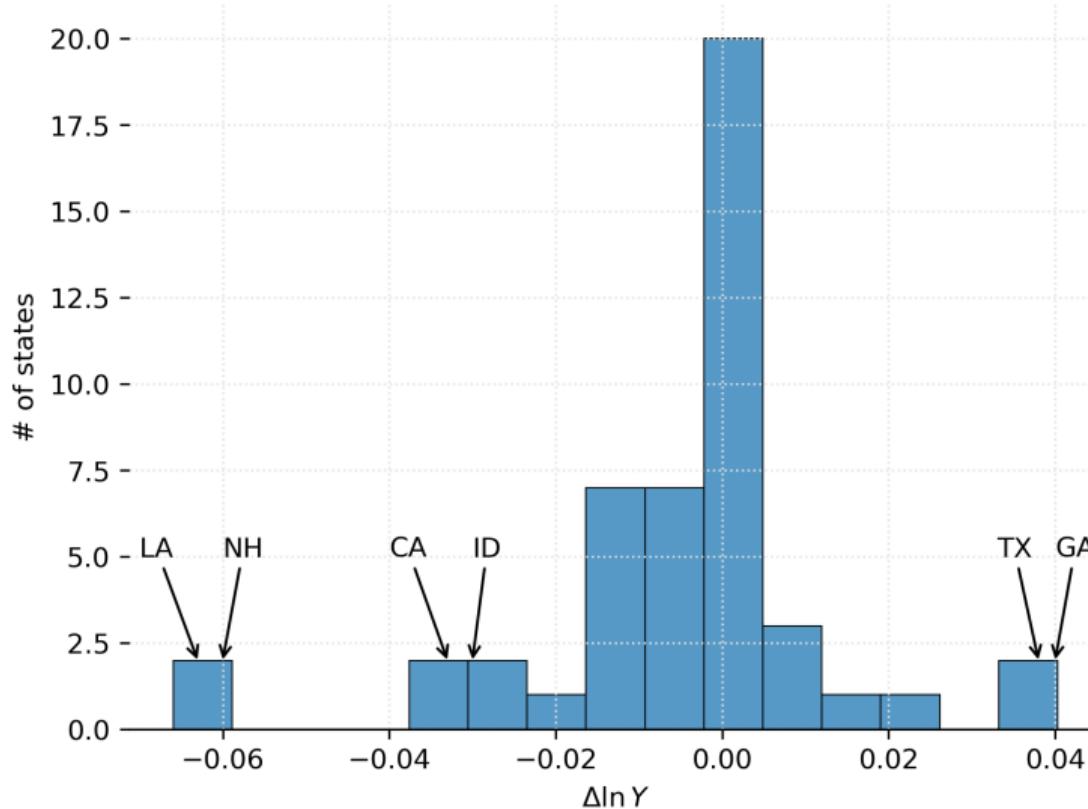
Figure: Short-run



Aggregate impact of local weather fluctuations

- Do the largest states like California, New York, and Texas generate the largest aggregate impact?
- Scenario: Aggregate effect of a local weather fluctuation:
 1. Weather shock at state n , $\tilde{\tau}_n^o = 1C$, while $\tilde{\tau}_m^o = 0, \forall m \neq n$
 2. $\tau_{jn}^{\text{network}}$ conditional on this set of weather fluctuations
 3. Compute impact at state level -> aggregate at national level.

Aggregate impact of local weather fluctuations



Robustness exercises

The previous analysis survives to:

- Using anomalies of minimum or maximum temperature. [Go](#)
- Changing the reference base to compute the trend (20 or 30 y.) [Go](#)
- Using sectoral GDP deflators instead of state-specific CPIs [Go](#)

CONCLUSIONS

- Heterogeneity and production networks amplify the estimated impact of weather anomalies in the short-run.
- Models without any of these characteristics underestimate the impact of a sudden increase in temperature by a factor of 3.
- The presence of inefficiencies may alter my estimates, and their inclusion is a source of future research.

APPENDIX

Common Factor Analysis

Counterfactual scenario II

- How likely is a widespread temperature increase across the United States?
- I propose a second counterfactual where the underlying drivers of these temperature anomalies are hit by a one-standard-deviation shock.
- A principal component analysis shows that two factors account for 80 percent of the variance of $\tilde{\tau}$
- One factor is associated with the eastern region and the other with the western.
- A shock of one standard deviation contracts the economic activity by 0.31 percent.

Common factor in temperature anomalies

I assume that temperature anomalies have underlying common factors

$$\tilde{\tau}_{nt} = \Lambda \tau_t^k + \epsilon_{\tilde{\tau},nt} \quad (9)$$

I filter the common factors τ_t^k using principal components

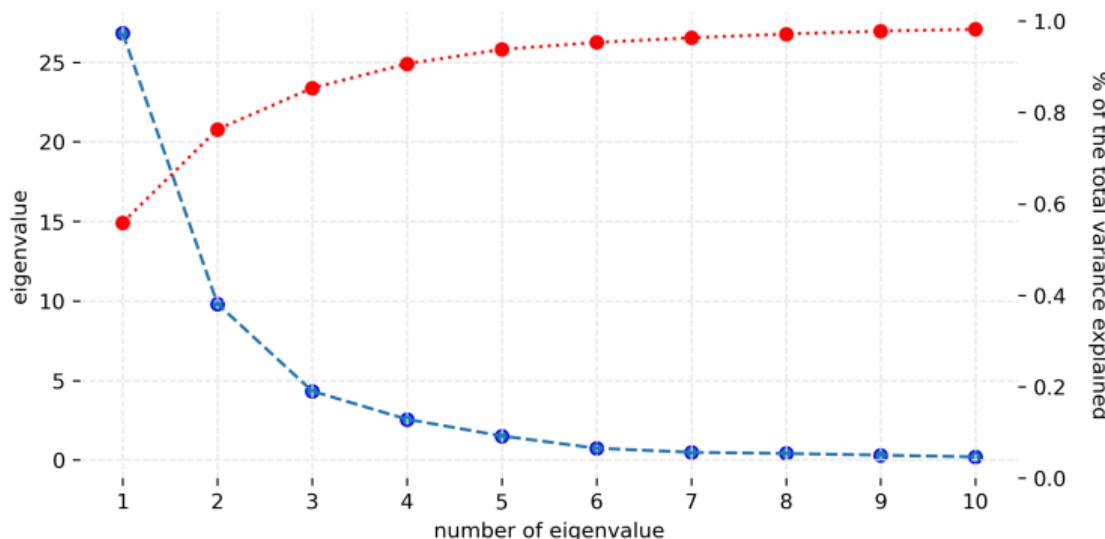


Figure: Factor analysis of weather fluctuations

Geographical distribution of common factors

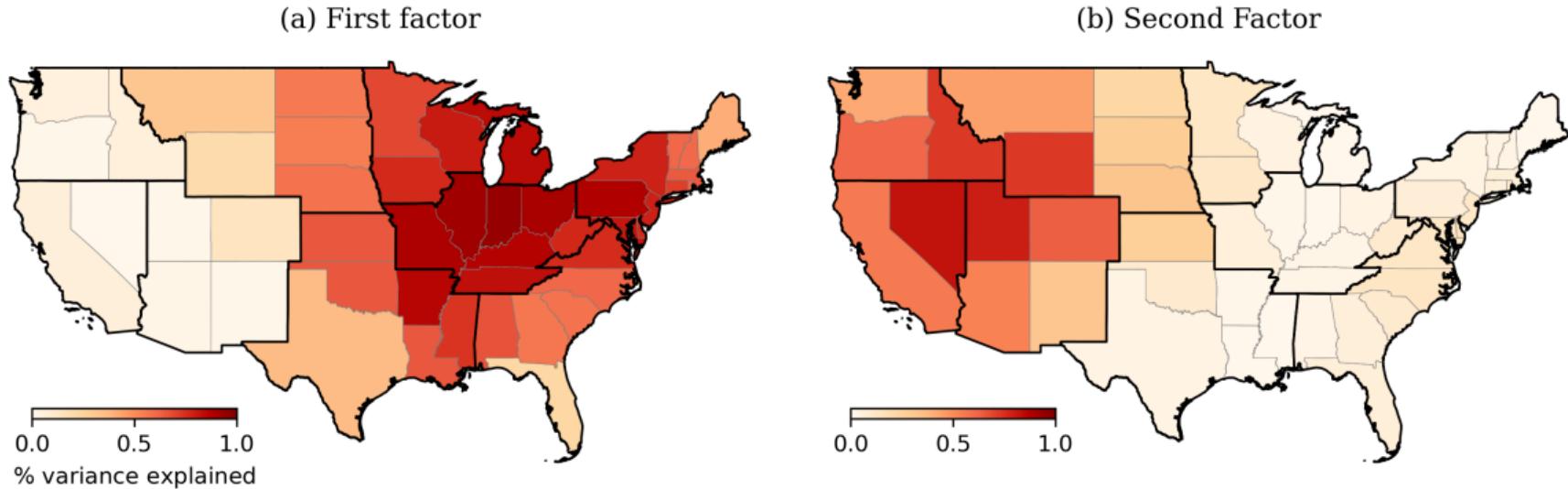
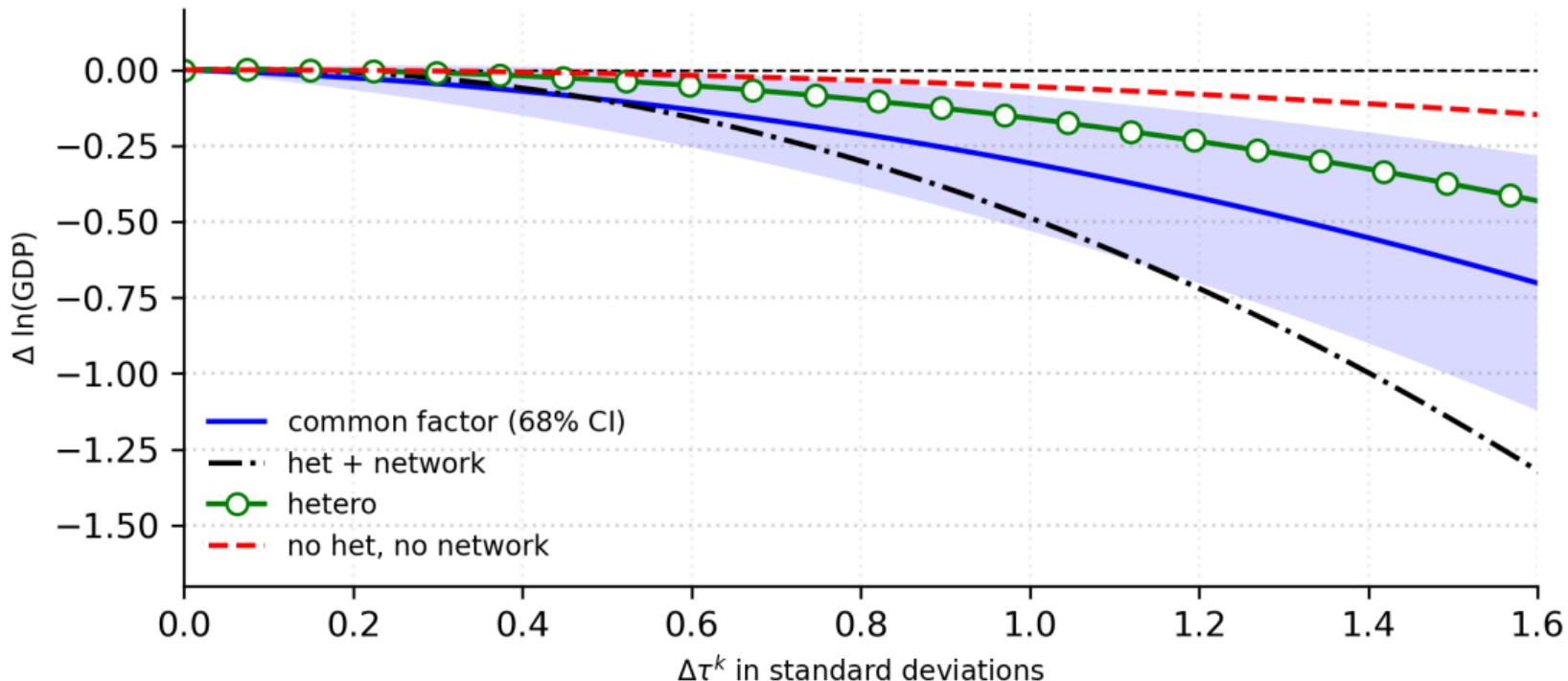


Figure: Contribution to $\sigma_{\tilde{\tau}}^2$ by state

Figure: Impact of a shock in τ_t^k on economic activity

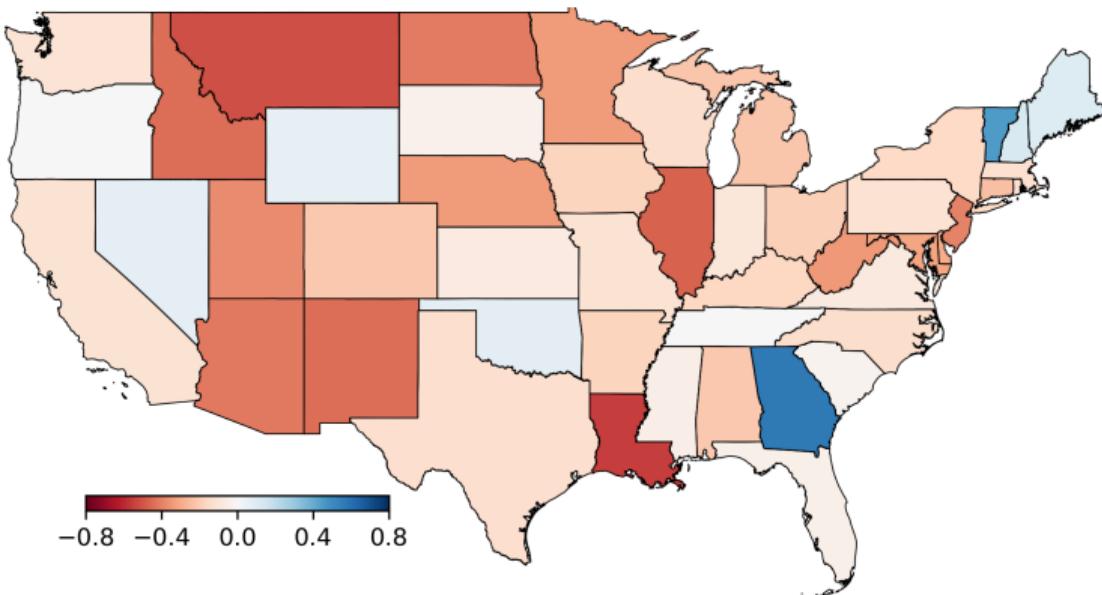
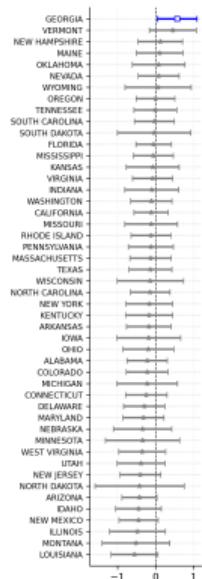


Expected impact of weather fluctuations in the LR

The expected effect of weather variability is: return

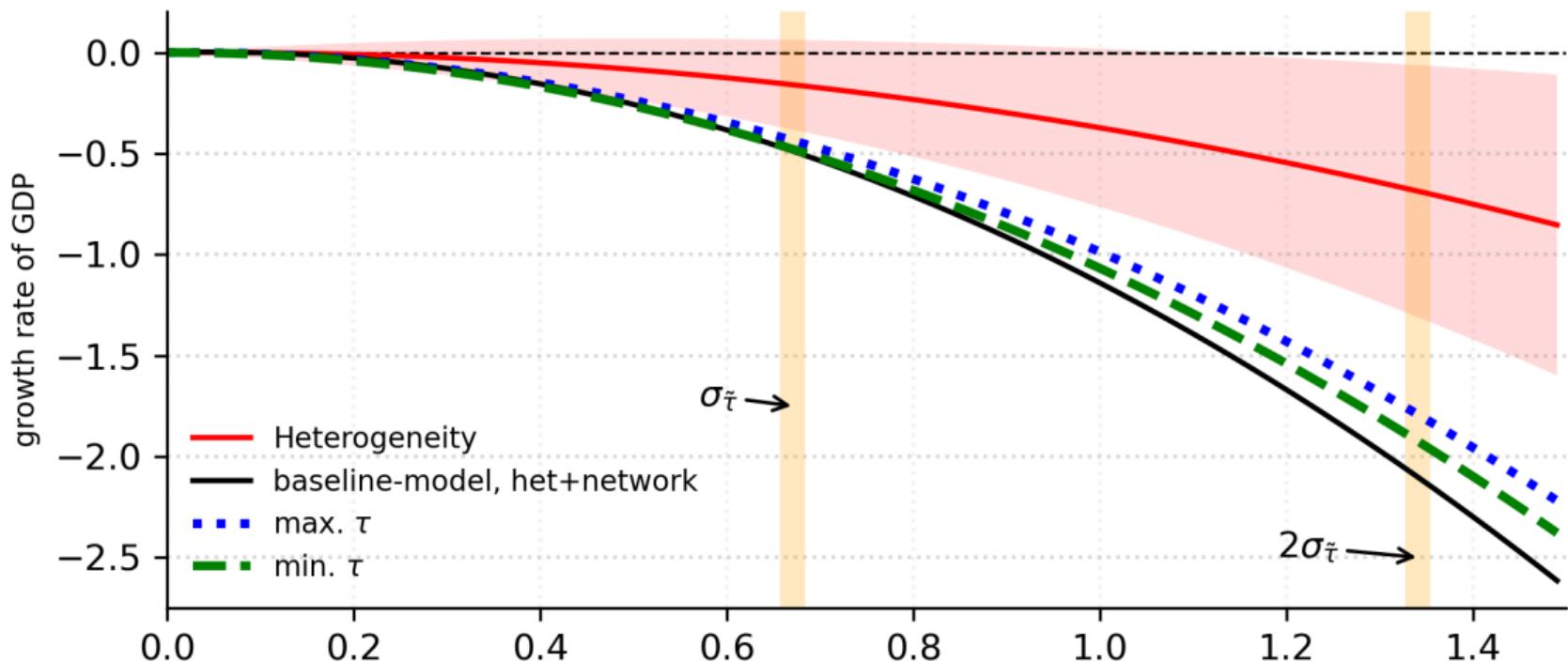
$$\mathcal{H}_{jn} = \mathbb{E}[\Delta y_{jnt}] - \mathbb{E}[\Delta y_{jnt} | \{\tilde{\tau}_{nt} = 0\}_{-\infty}] = \frac{\hat{\delta}_{2n} + \hat{\gamma}_{2j}}{1 - \hat{\rho}_j} \sigma_{\tilde{\tau}_n}^2$$

Figure: Contribution of weather variability to growth rates at state level \mathcal{H}_n



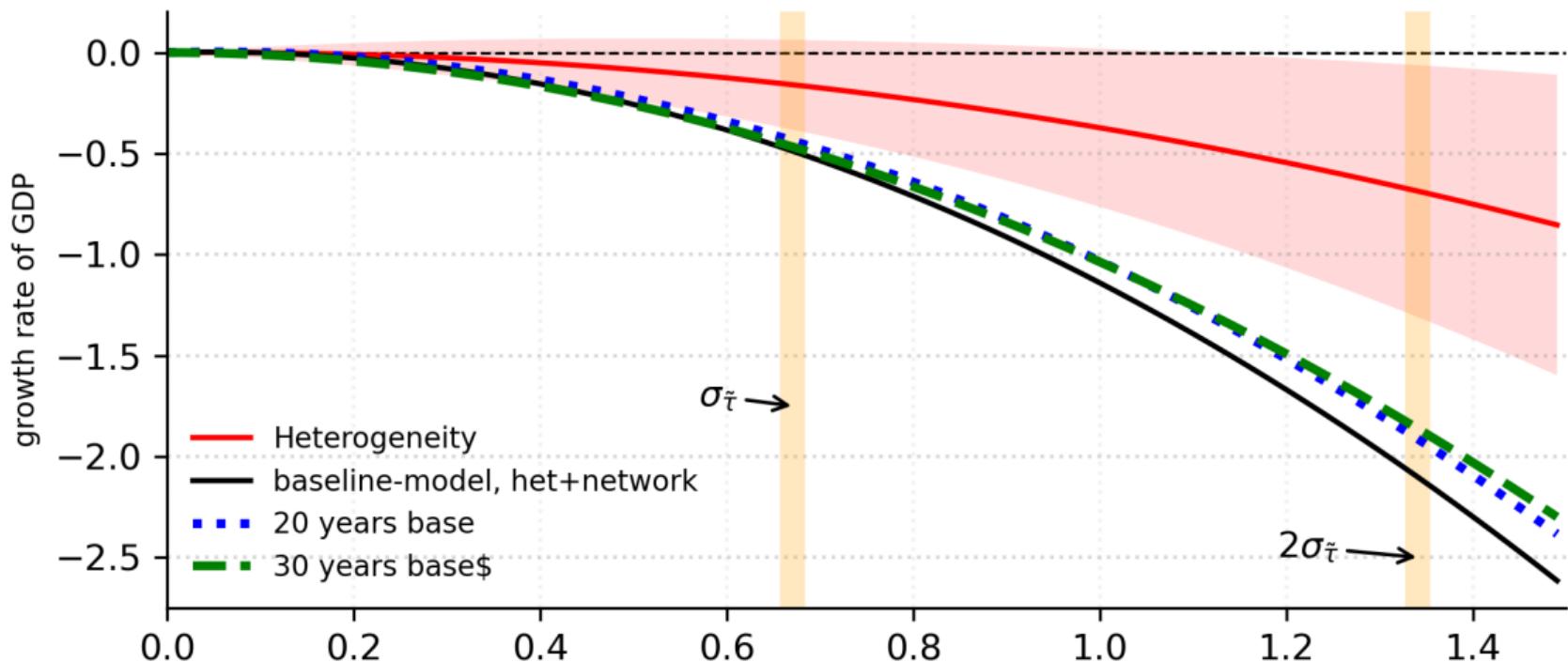
Robustness Analysis

Figure: Economic impact of a generalized shock in $\tilde{\tau}$



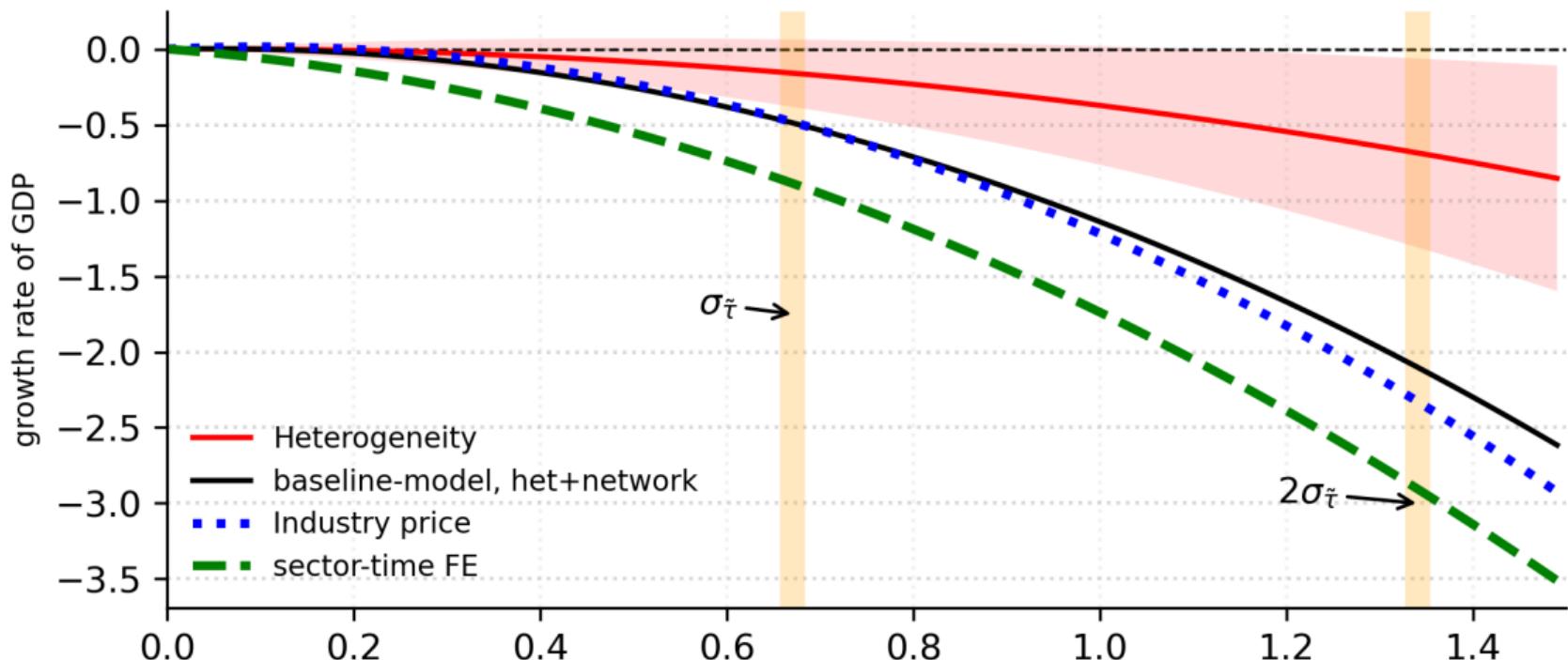
return

Figure: Economic impact of a generalized shock in $\tilde{\tau}$



return

Figure: Economic impact of a generalized shock in $\tilde{\tau}$



return

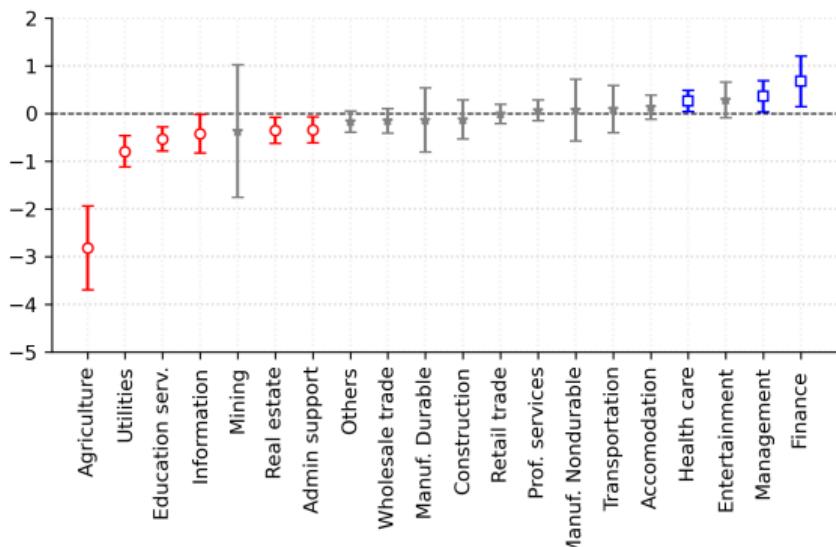
Additionals

Impact of $\tilde{\tau}$ at industry level

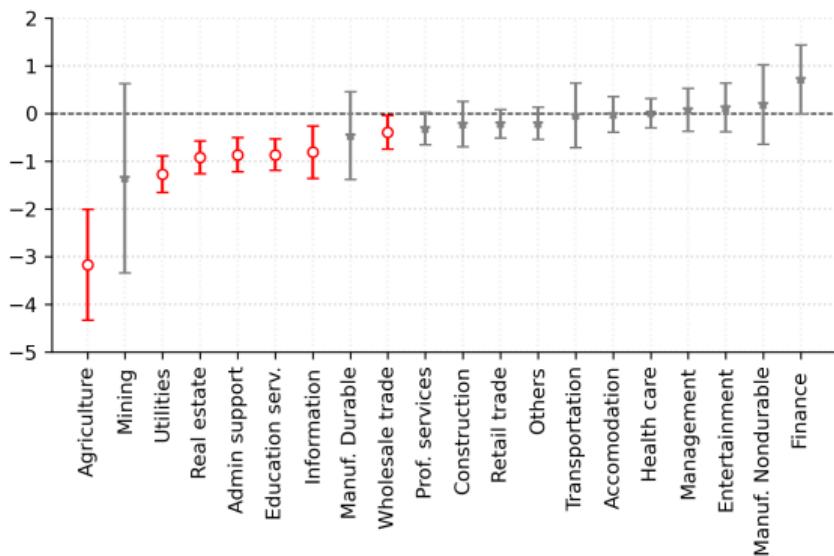
Industry level: $\mathcal{G}_l(\tilde{\tau}_{n,t}^o) = \sum_g w_{ln}^b \mathcal{G}_{ln}(\tilde{\tau}_{n,t}^o),$

$$w_{ln}^b = \frac{1}{T} \sum_t \left(\frac{\text{nom, GSP}_{ln}}{\sum_g \text{nom GSP}_{ln}} \right)_t$$

(a) Small weather shock

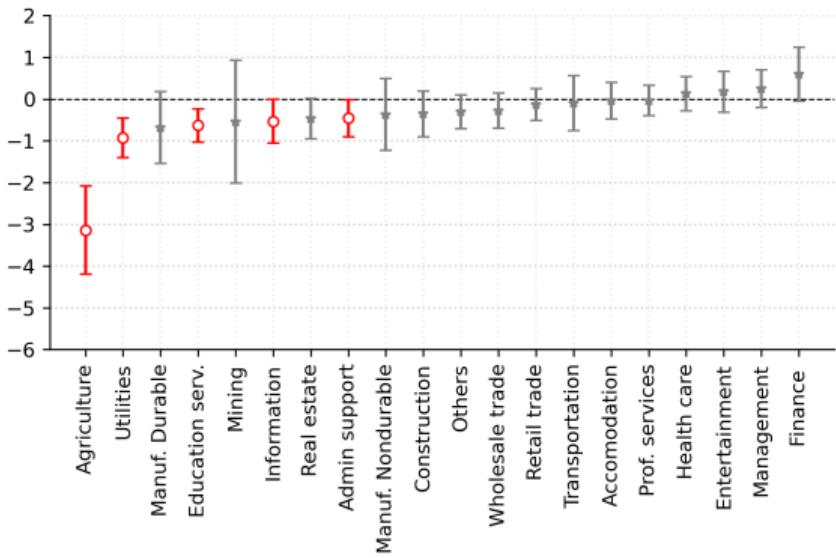


(b) Large weather shock

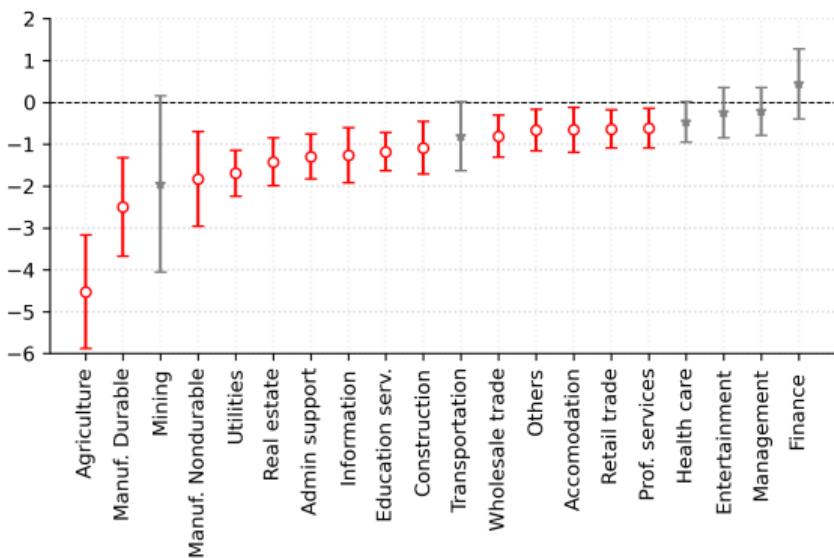


Impact of $\tilde{\tau}$ by industry: Networks

(a) Small weather shock



(b) Large weather shock

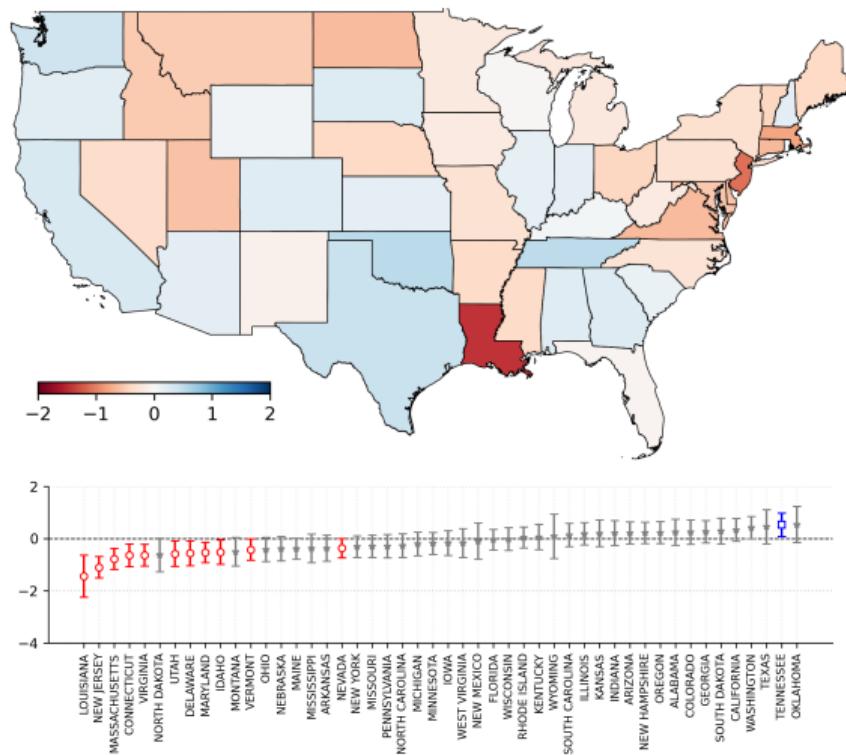


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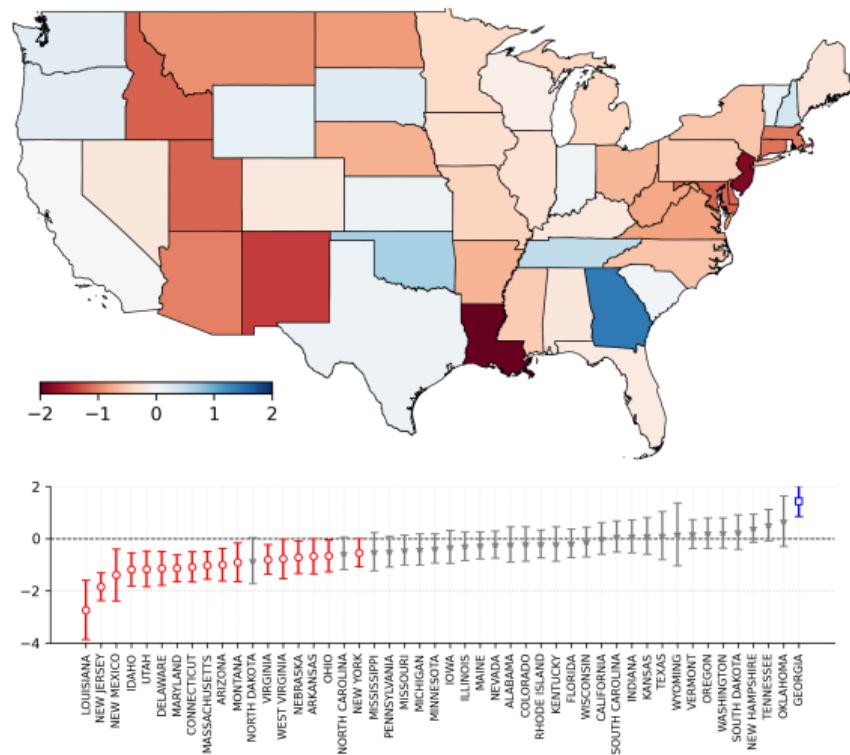
Impact of $\tilde{\tau}$ at state level

[return](#)

(a) Small weather shock



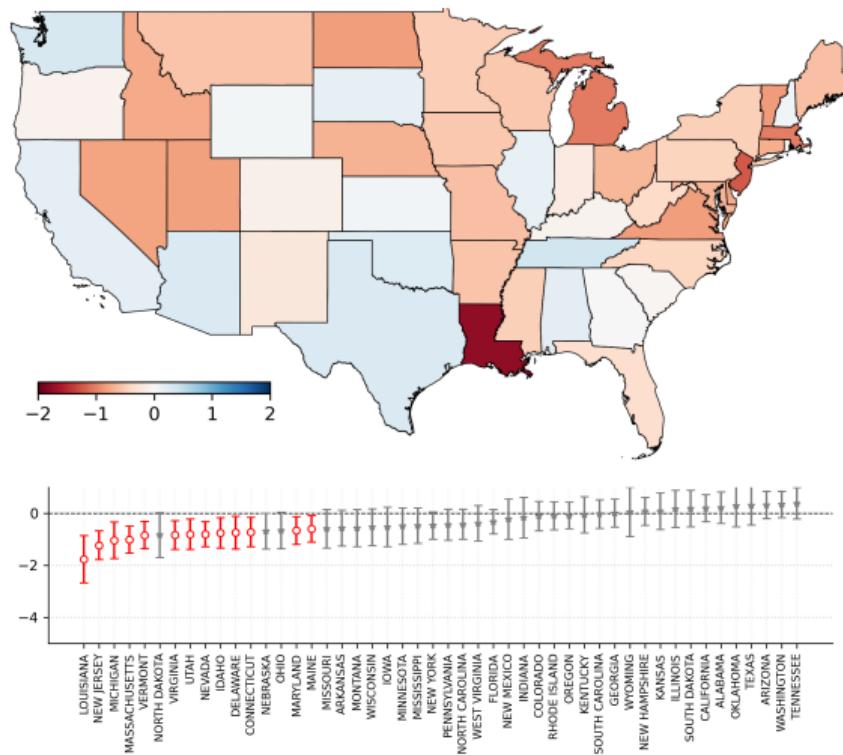
(b) Large weather shock



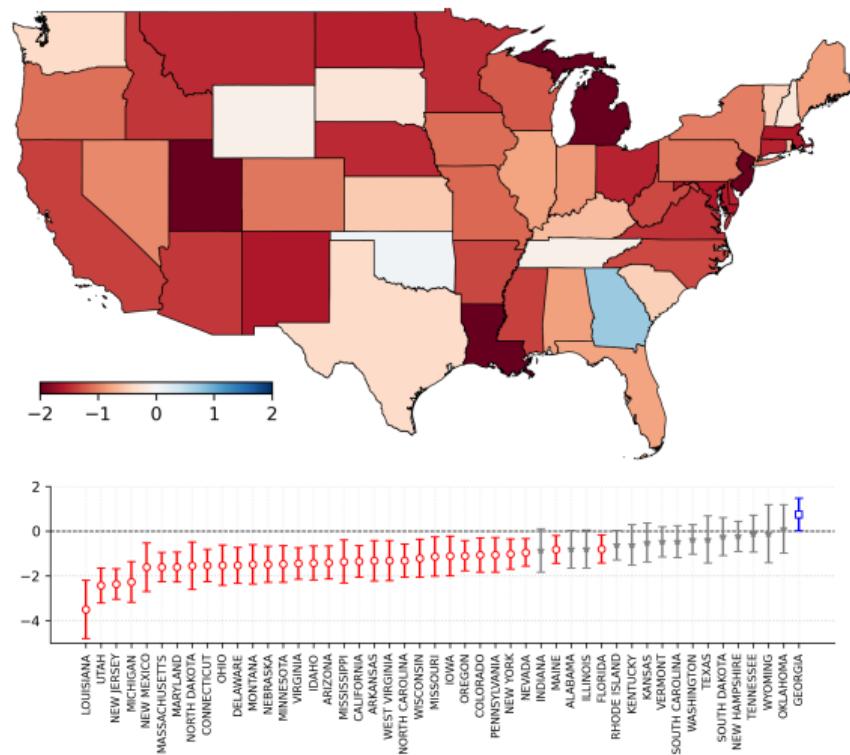
Impact of $\tilde{\tau}$ at state level

[return](#)

(a) Small weather shock



(b) Large weather shock



Data for calibration: more

- USE table:

- Let $\tilde{a}_{ji} = \frac{p_i x_{ji}}{p_j y_j}$ be the average requirements of sector j on goods i

- Commodity Flow Survey:

- How much of a good i , a state m sold to state n : $b_j^{n,m}$
 - I construct the share of state m in the expenditures of state n on good i :

$$\tilde{b}_{,i}^{n,m} = \frac{b_{,i}^{n,m}}{\sum_h b_{,i}^{n,h}}$$

- I approximate the elements of A as:

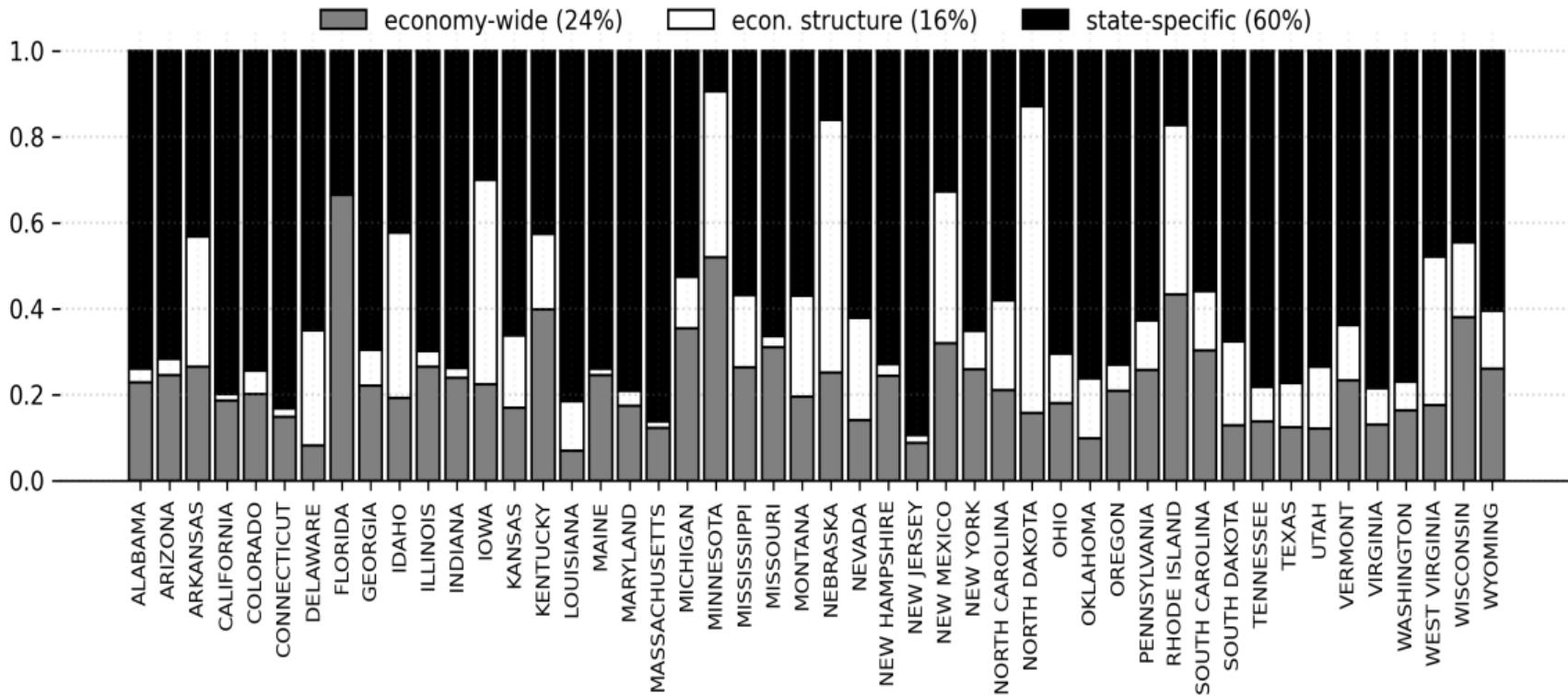
$$\mathcal{A}_{j,i}^{n,m} = \tilde{b}_{,i}^{n,m} \tilde{a}_{ji}$$

- When the state n buys good i , the fraction used as input is independent of the state from where the product comes

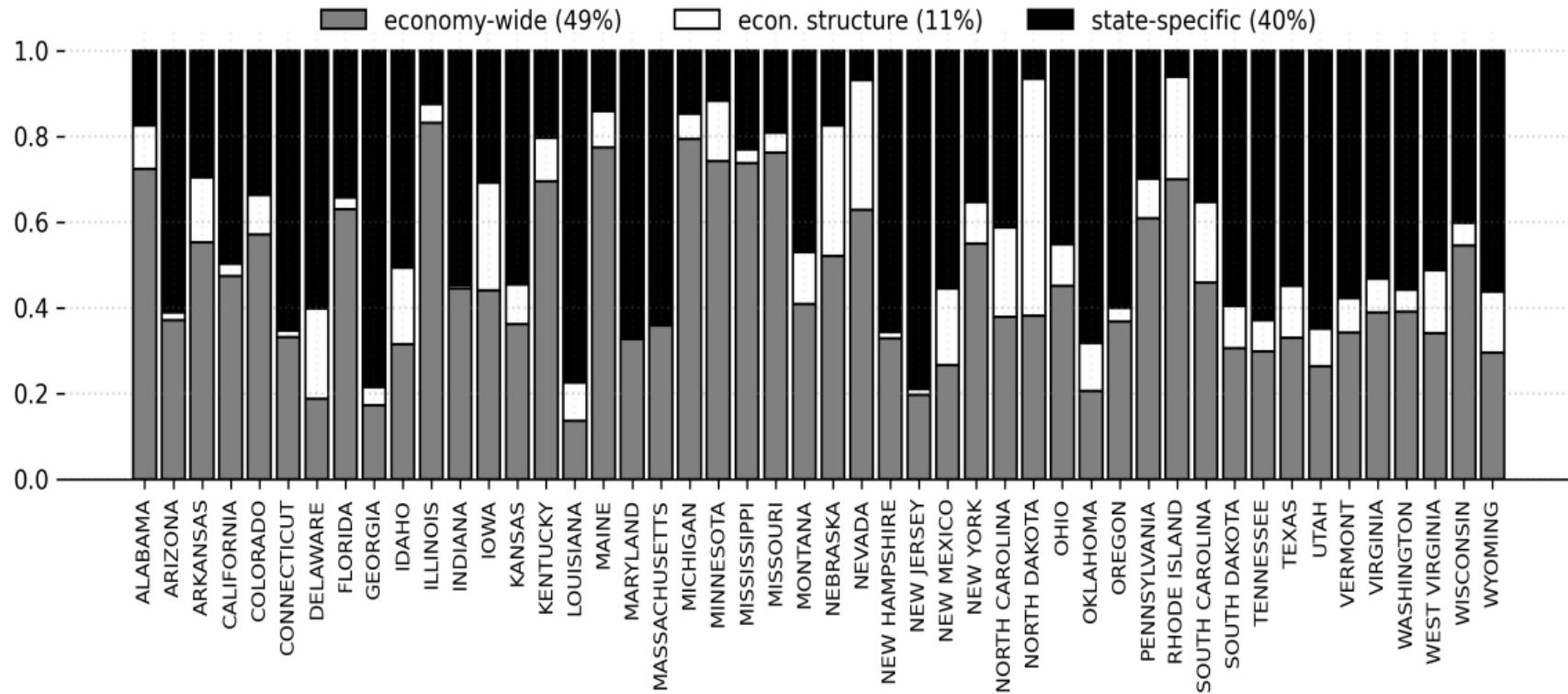
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Small weather shock

[return](#)



Large weather shock



Direct vs indirect exposure

[return](#)

Figure: Small weather shock

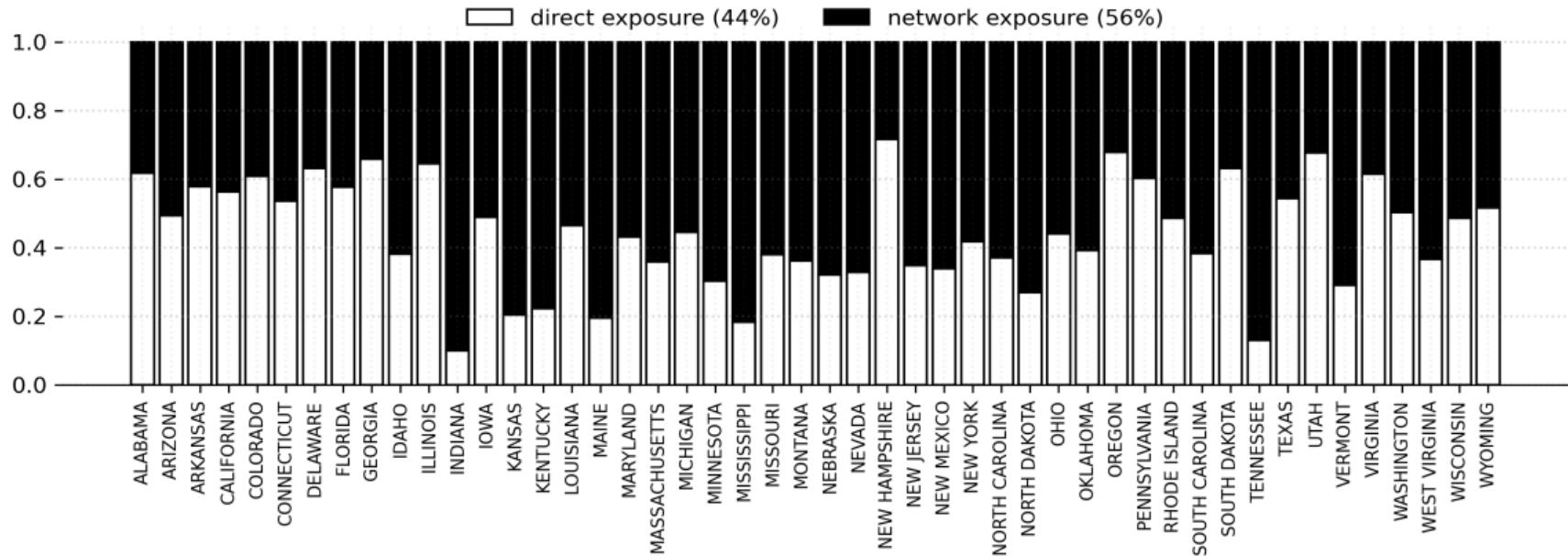
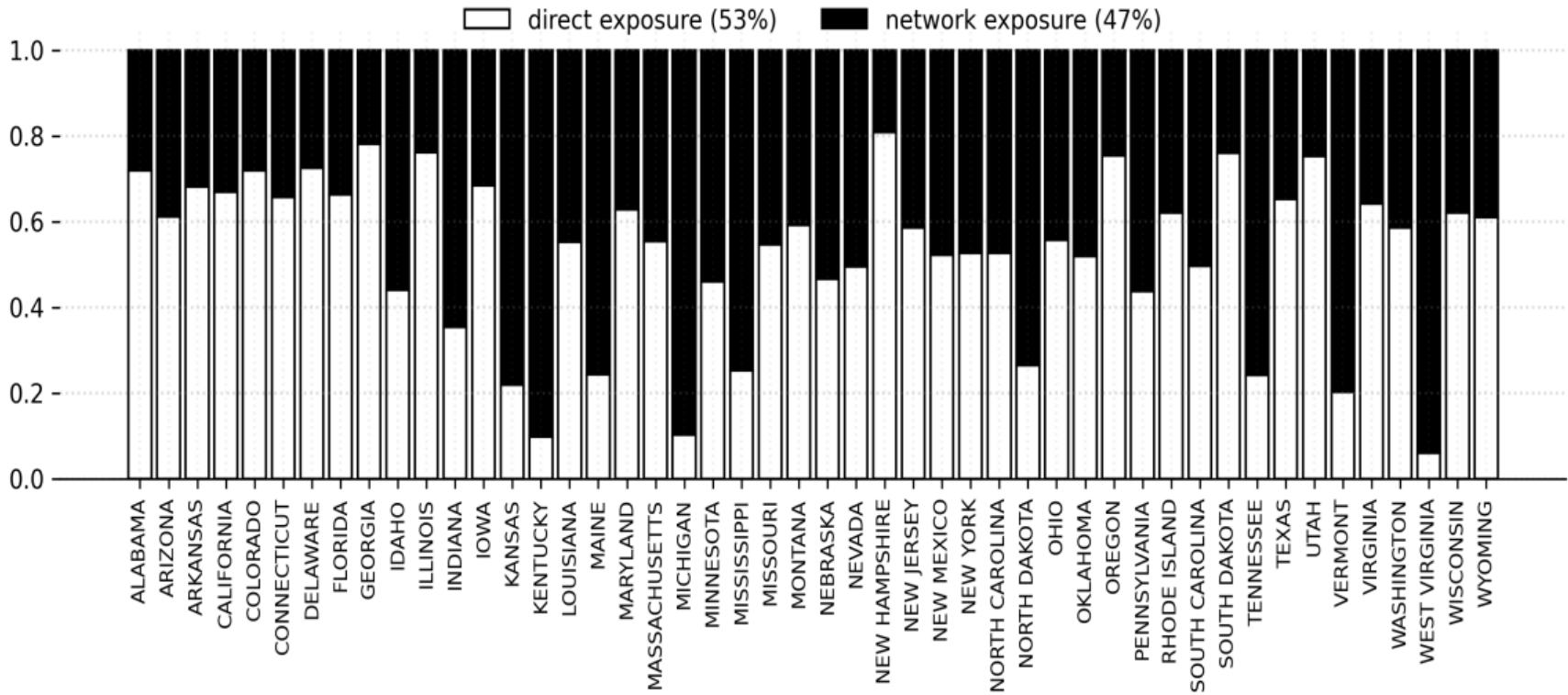
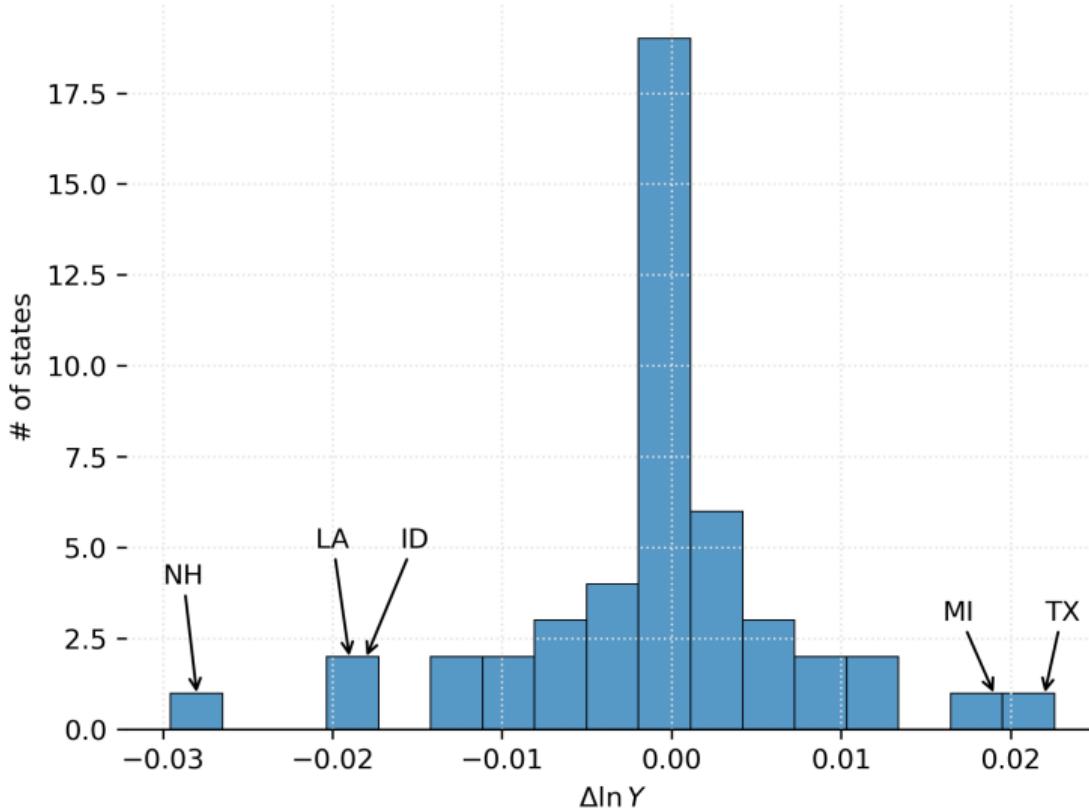


Figure: Large weather shock



Aggregate impact of local weather fluctuations: $\sigma_{\tilde{\tau}_n}$



References I

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