

# 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:

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

- $\beta_n$  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 :

- $\Delta y_{jnt}$ : 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.
- $\rho_j$  includes some dynamics.
- $\theta_n$  and  $\theta_j$  are state-specific and sector-specific slopes, respectively.

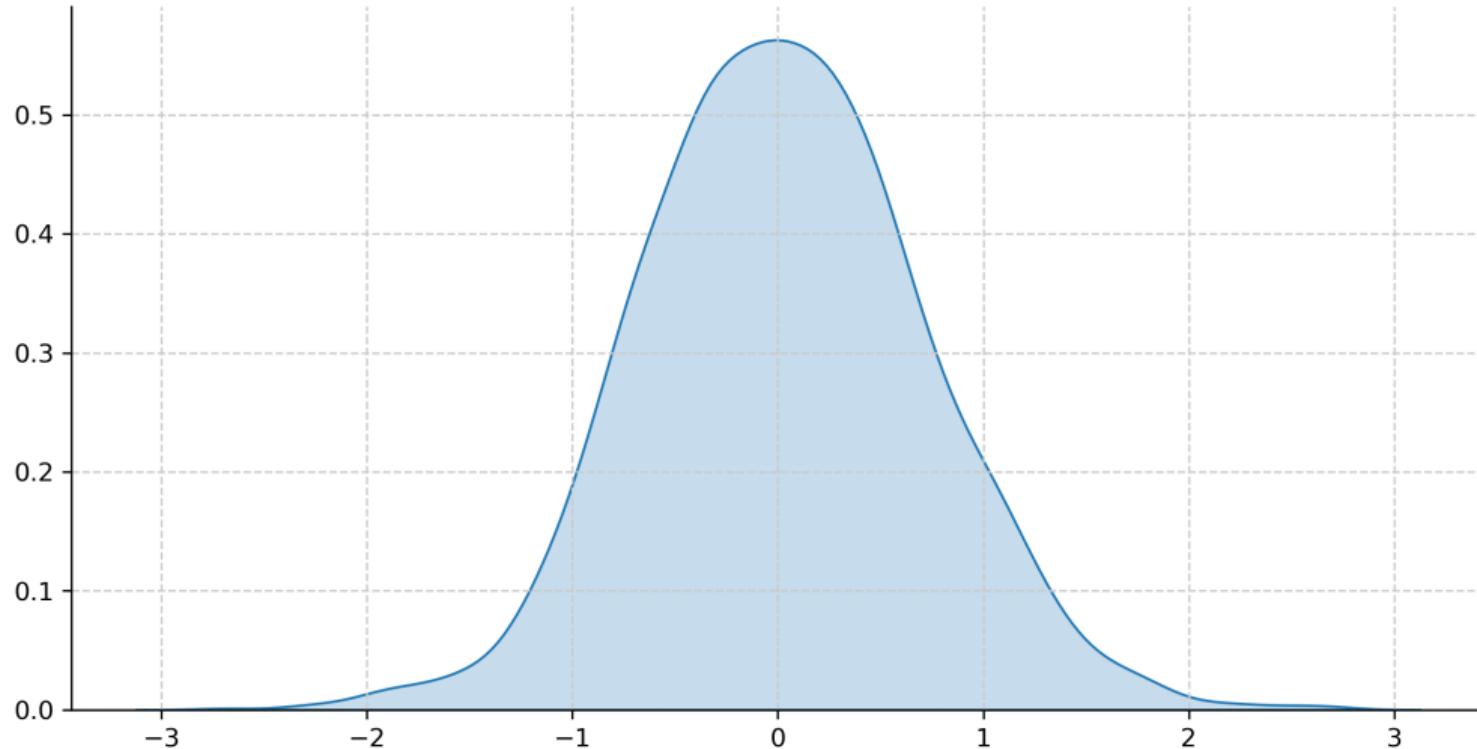
## Data:

- 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)

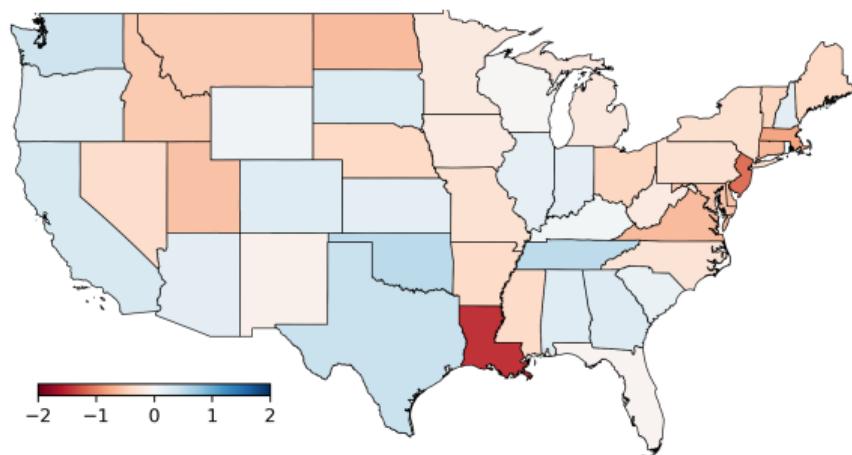
**State level:**  $\mathcal{G}_n(\tilde{\tau}_{n,t}^o) = \sum_j w_{jn} \mathcal{G}_{jn}(\tilde{\tau}_{n,t}^o), \quad w_{jn} = \frac{1}{T} \sum_t \left( \frac{\text{nom GSP}_{jn}}{\sum_j \text{nom GSP}_{jn}} \right)_t$

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

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

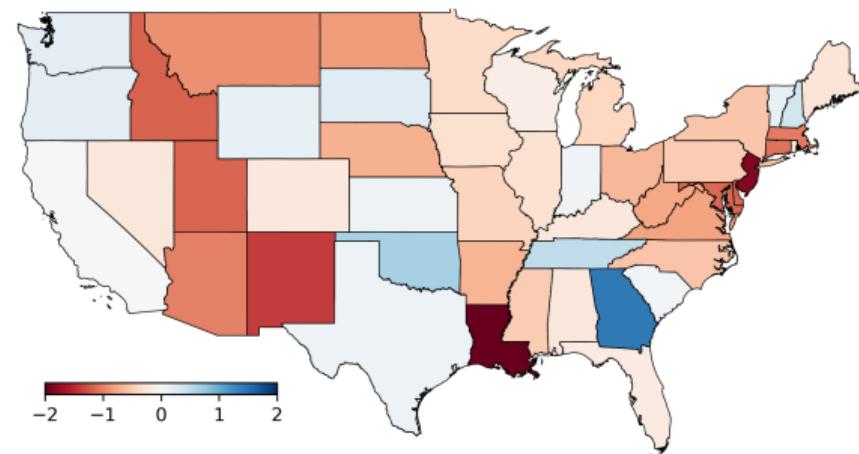
confidence

(a) Small weather shock



Industry level

(b) Large weather shock



# Decomposing $\mathcal{G}_n$

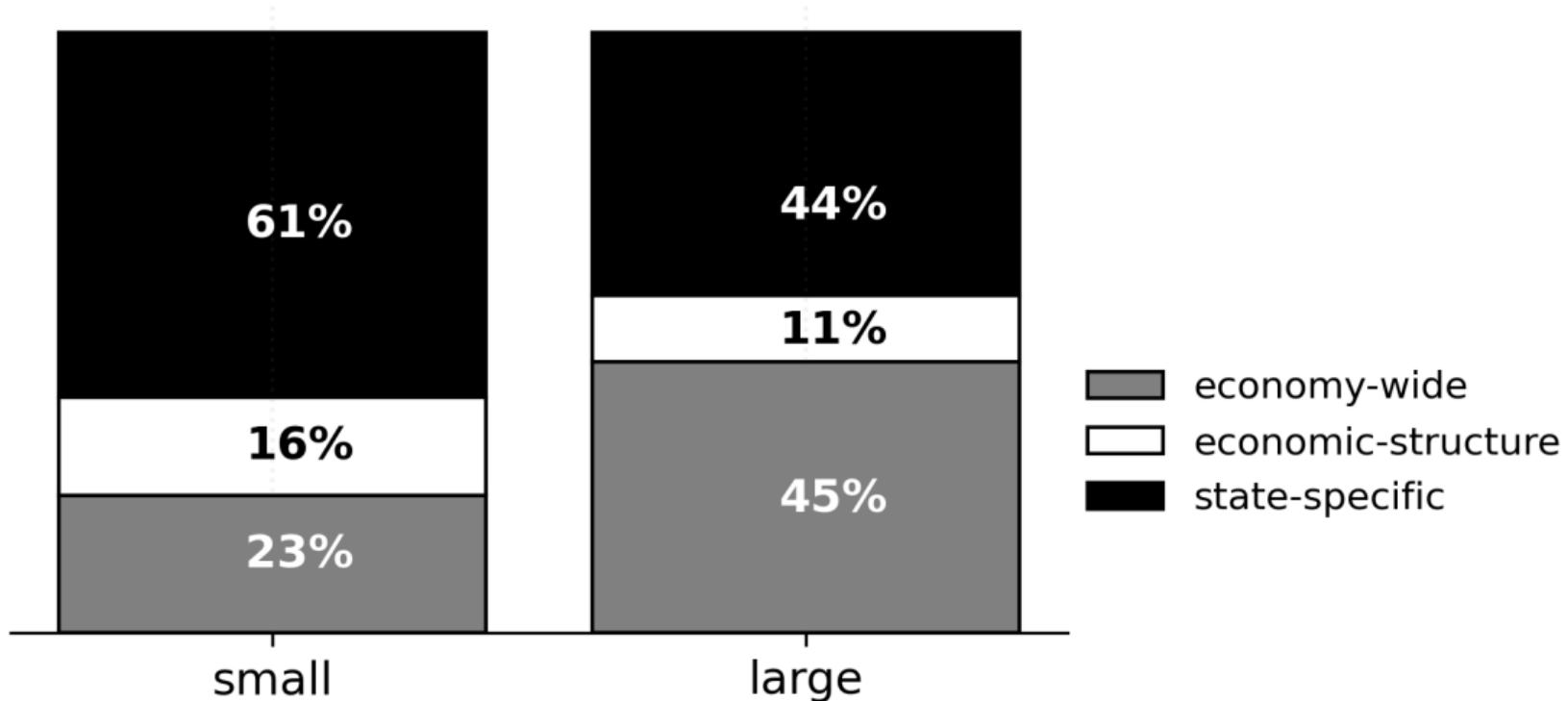
- How much of the differences across states are due to sectoral composition?
- We can decompose the state-level result  $\mathcal{G}_n$  in:

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

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

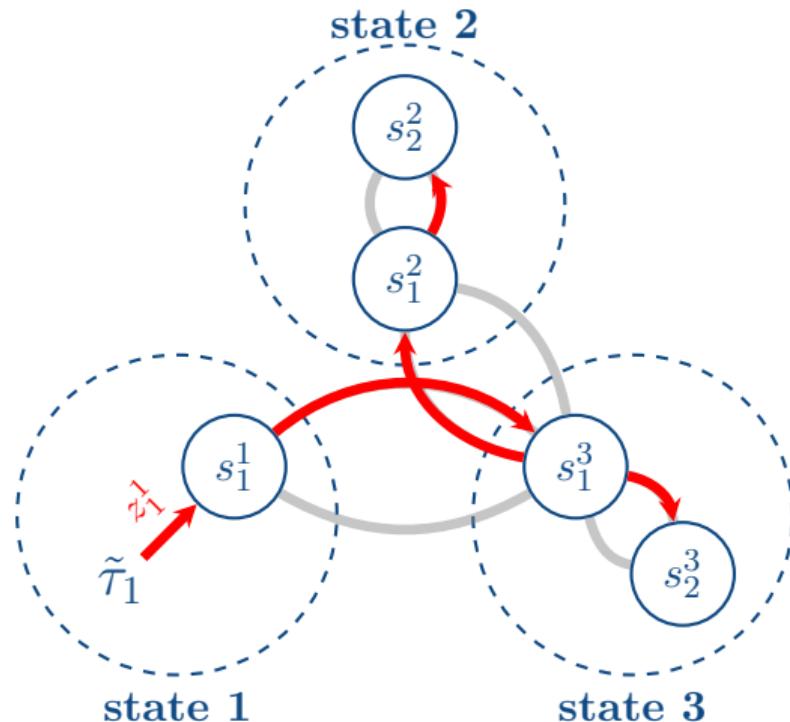
$$q_n = c_n + \sum_{m,j} x_{mn}^j \quad \forall n$$

- 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
- $\tilde{\tau}_{jnt}^{network}$  has 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:

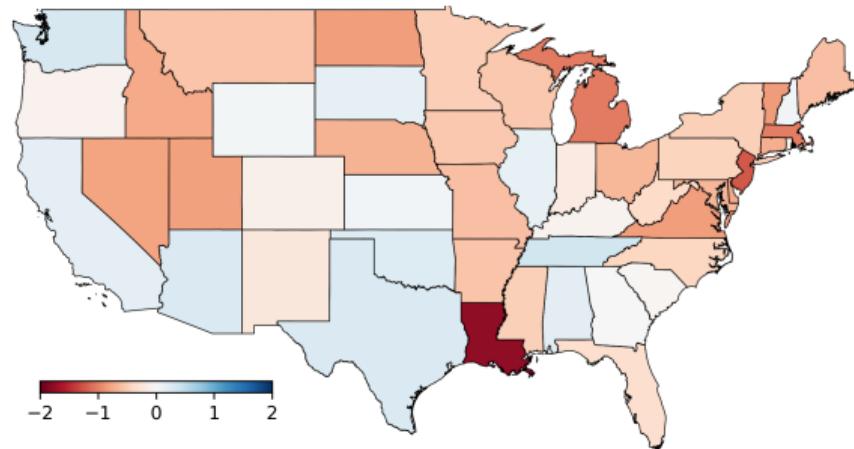
$$\mathcal{G}_n(\tilde{\tau}_{n,t}^o) = \sum_j w_{jn} \mathcal{G}_{jn}(\tilde{\tau}_{n,t}^o)$$

no data on gross output at sector-state level.

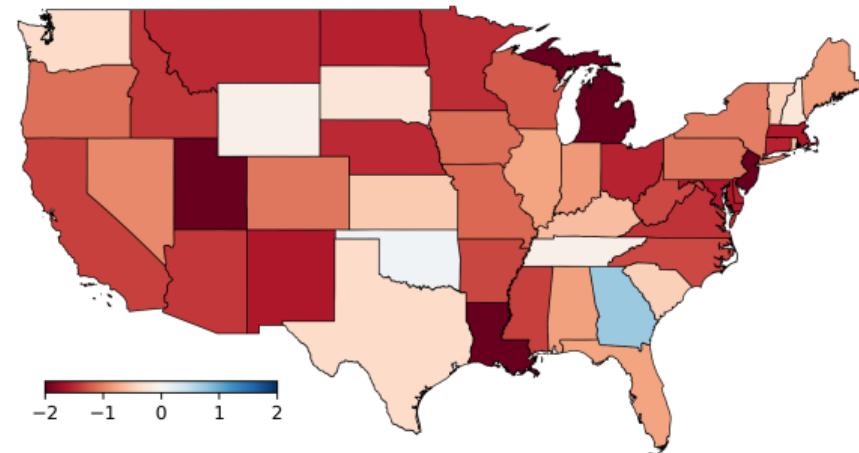
# Impact of $\tilde{\tau}$ by state

confidence

(a) Small weather shock



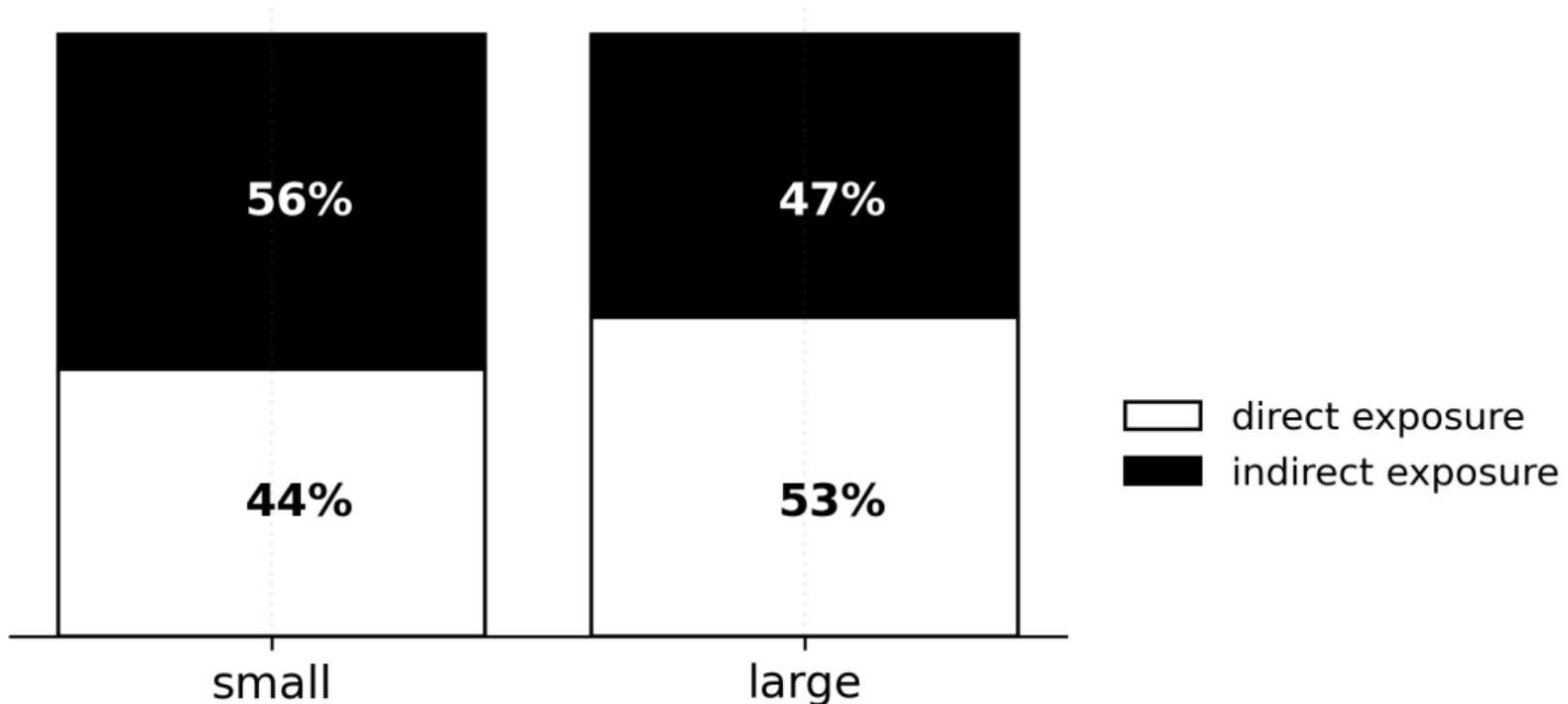
(b) Large weather shock



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 production networks

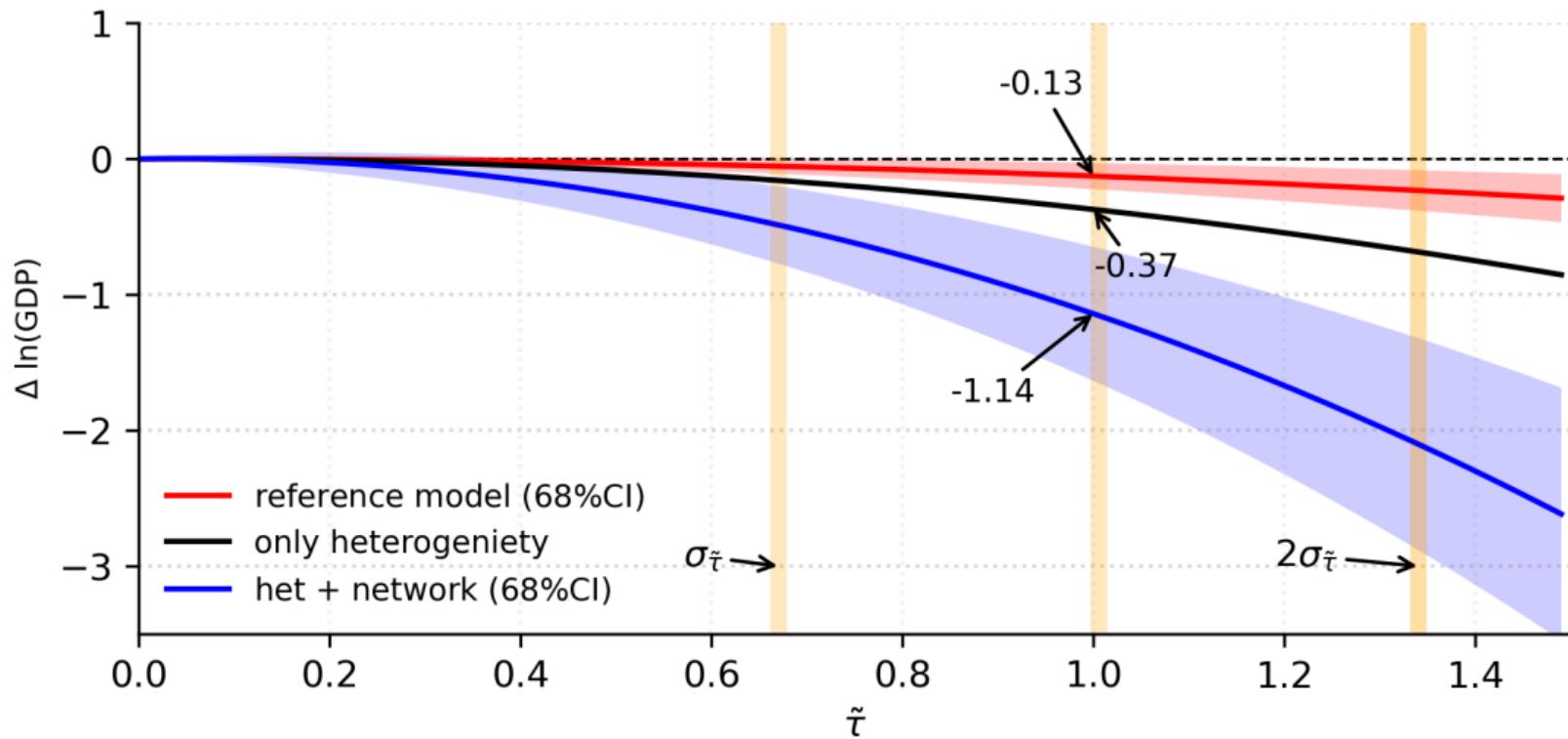
$$\sum_n w_n \mathcal{G}_n^{\text{network}}(\tilde{\tau}^o) \tilde{\tau}^o$$

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

## 3. Reference model for comparison:

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

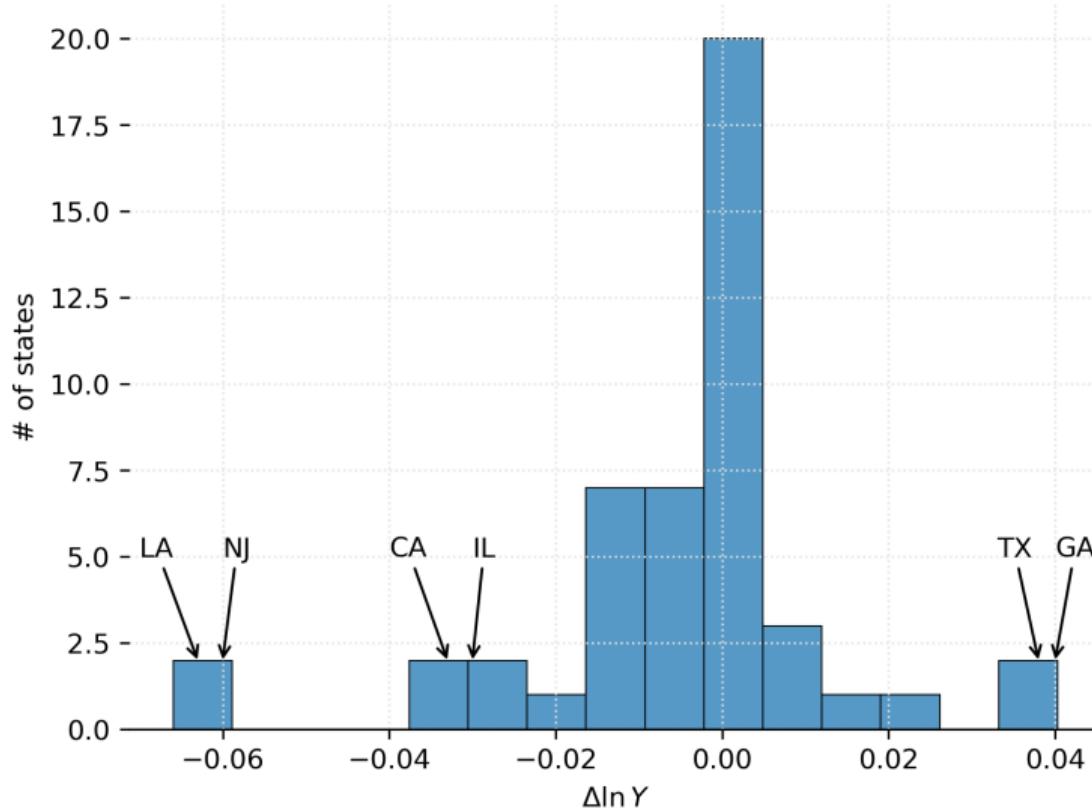
# Aggregate impact of an weather fluctuations $\tilde{\tau}$



## 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  $\tau_t^k$  using principal components

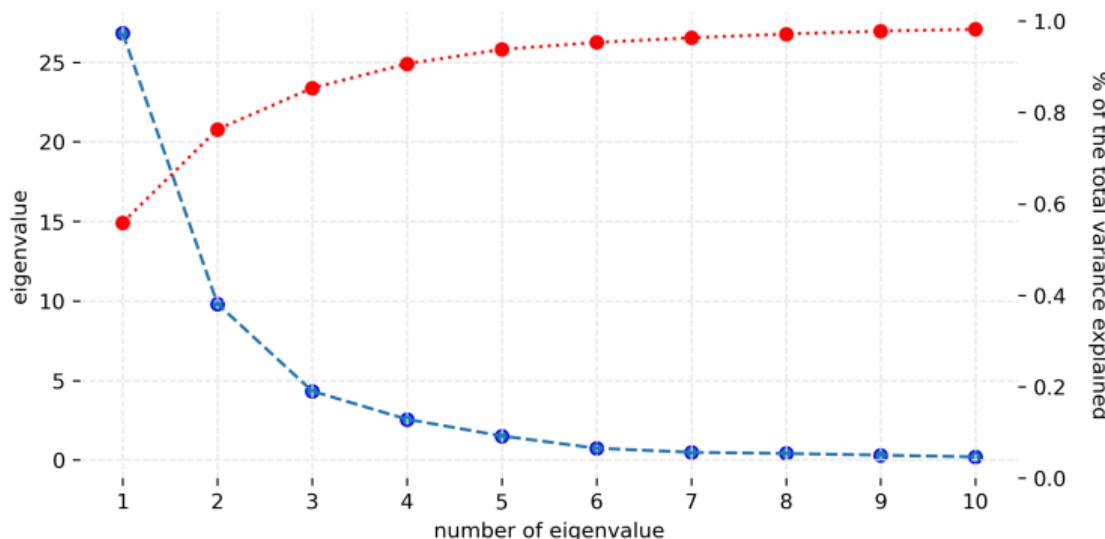


Figure: Factor analysis of weather fluctuations

# Geographical distribution of common factors

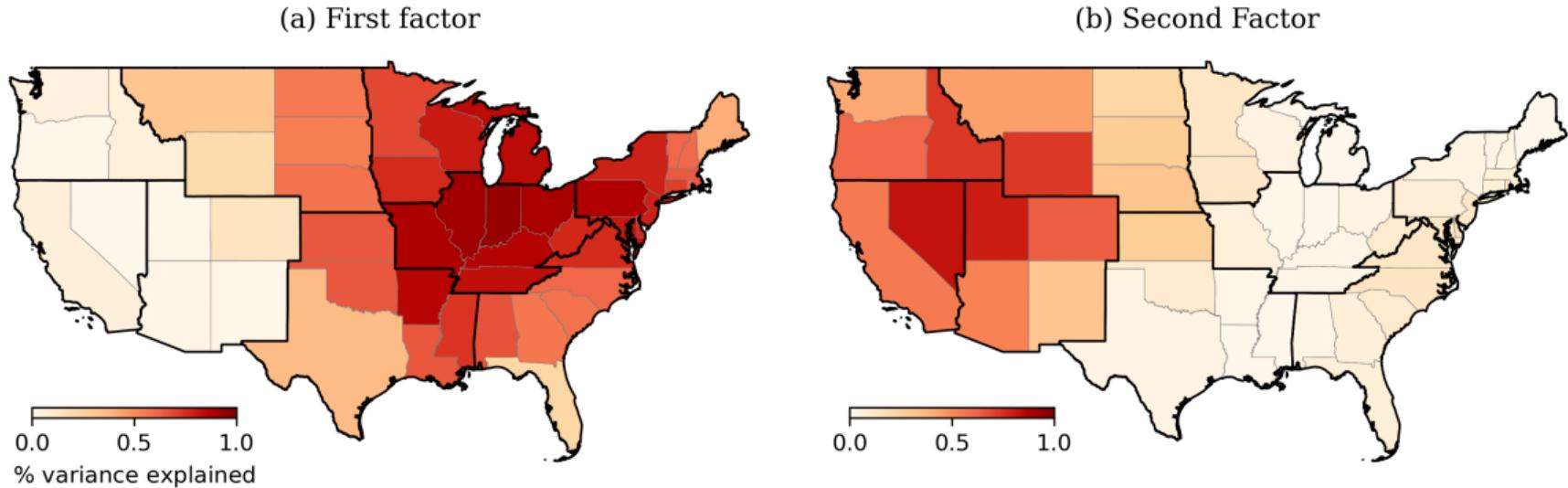
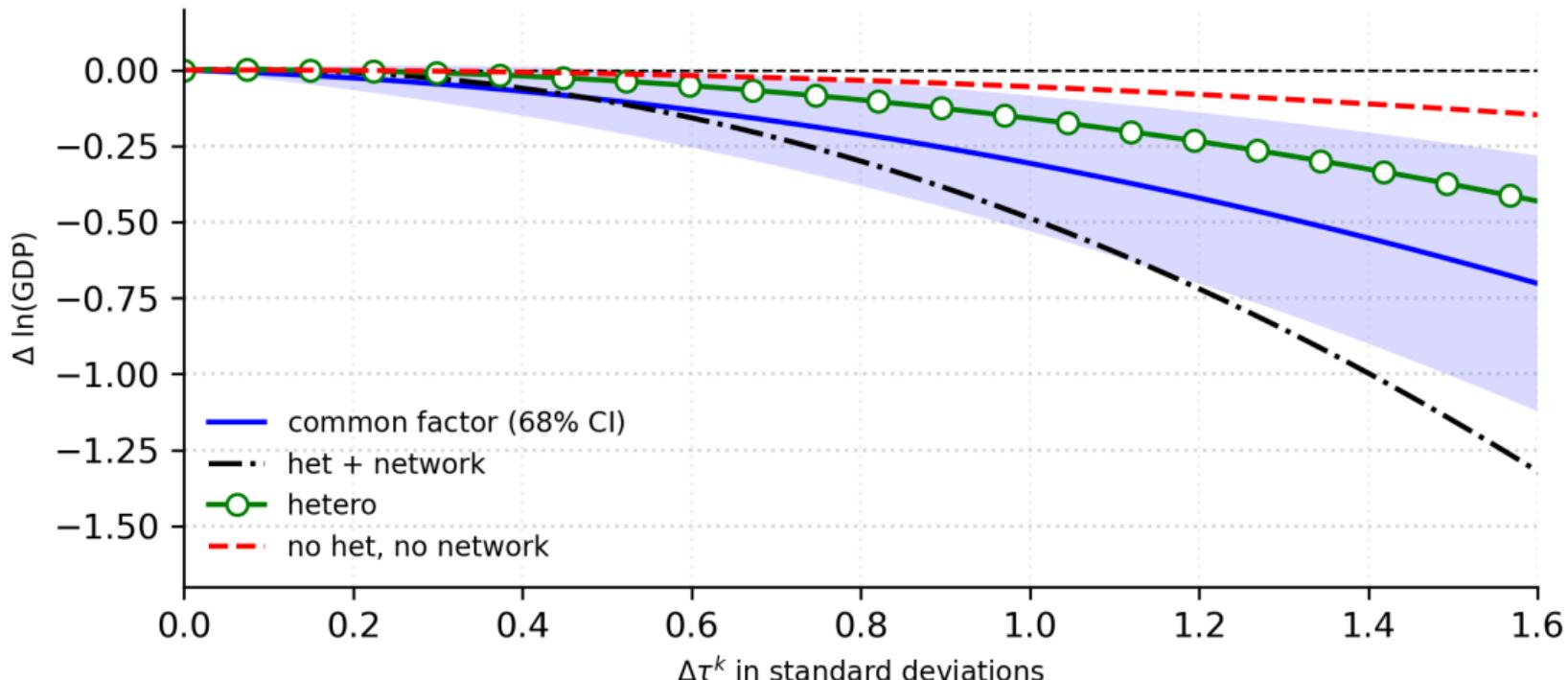


Figure: Contribution to  $\sigma_{\tilde{\tau}}^2$  by state

Figure: Impact of a shock in  $\tau_t^k$  on economic activity

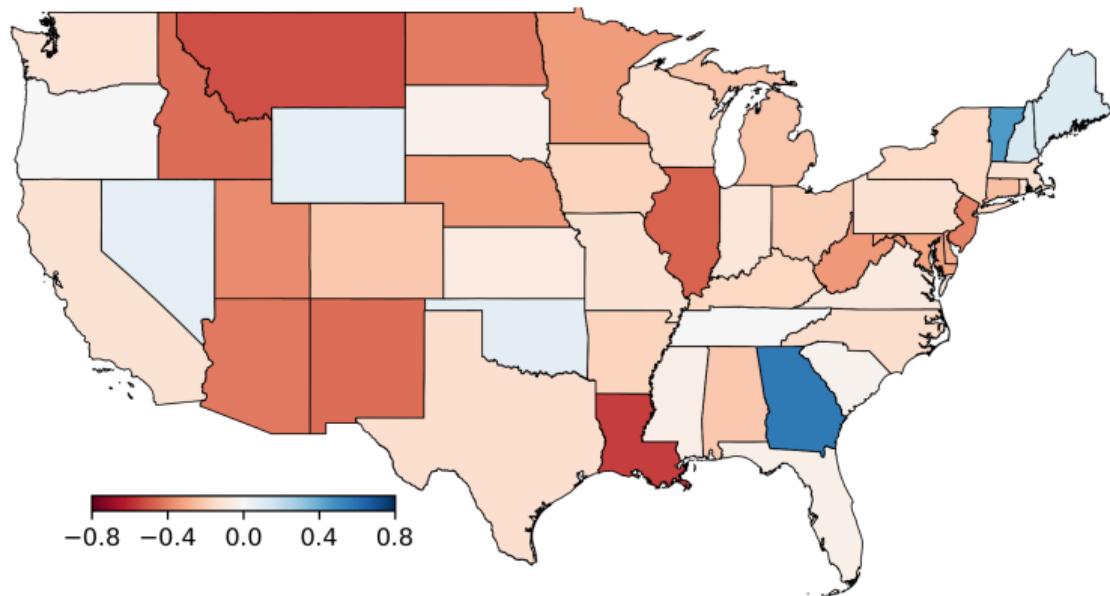
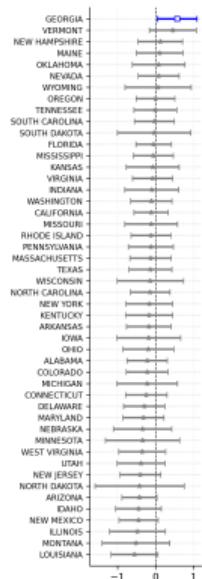


# Expected impact of weather fluctuations in the LR

The expected effect of weather variability is: return

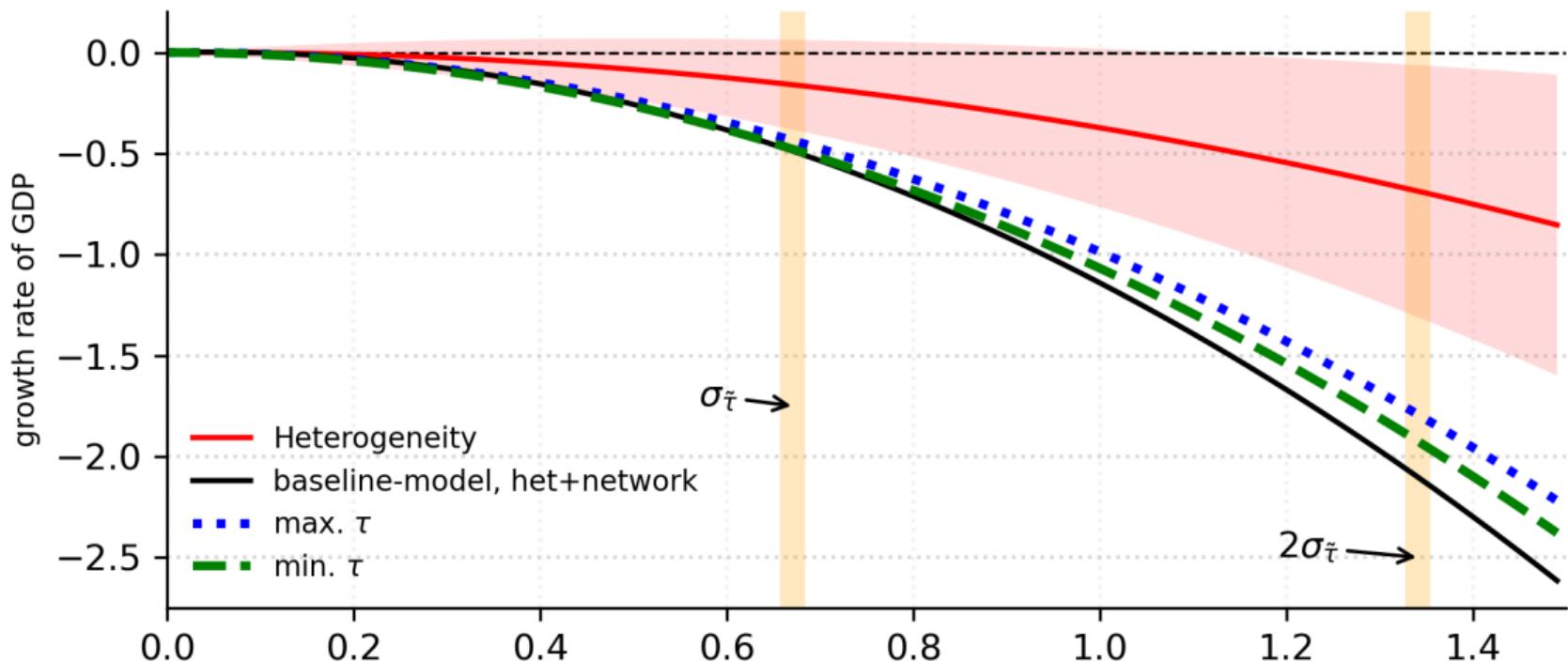
$$\mathcal{H}_{jn} = \mathbb{E}[\Delta y_{jnt}] - \mathbb{E}[\Delta y_{jnt} | \{\tilde{\tau}_{nt} = 0\}_{-\infty}] = \frac{\hat{\delta}_{2n} + \hat{\gamma}_{2j}}{1 - \hat{\rho}_j} \sigma_{\tilde{\tau}_n}^2$$

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



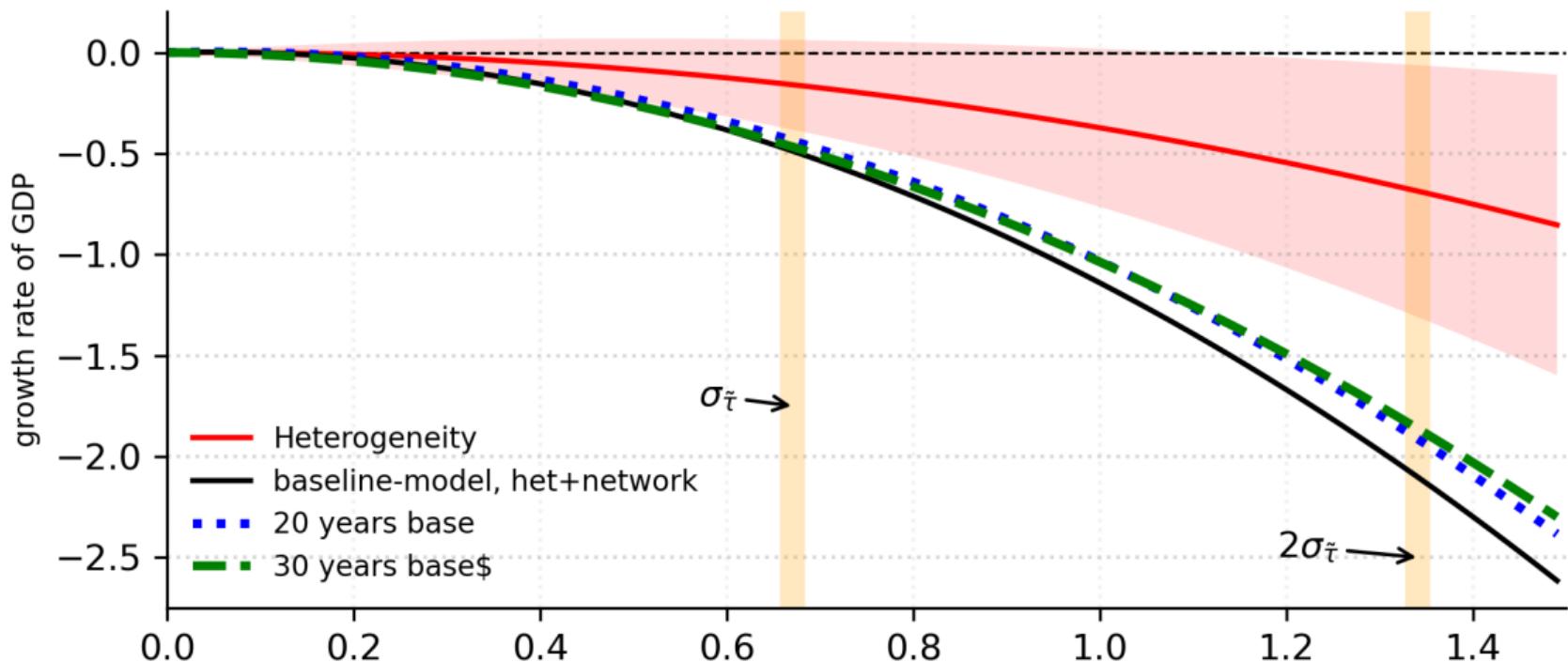
# Robustness Analysis

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



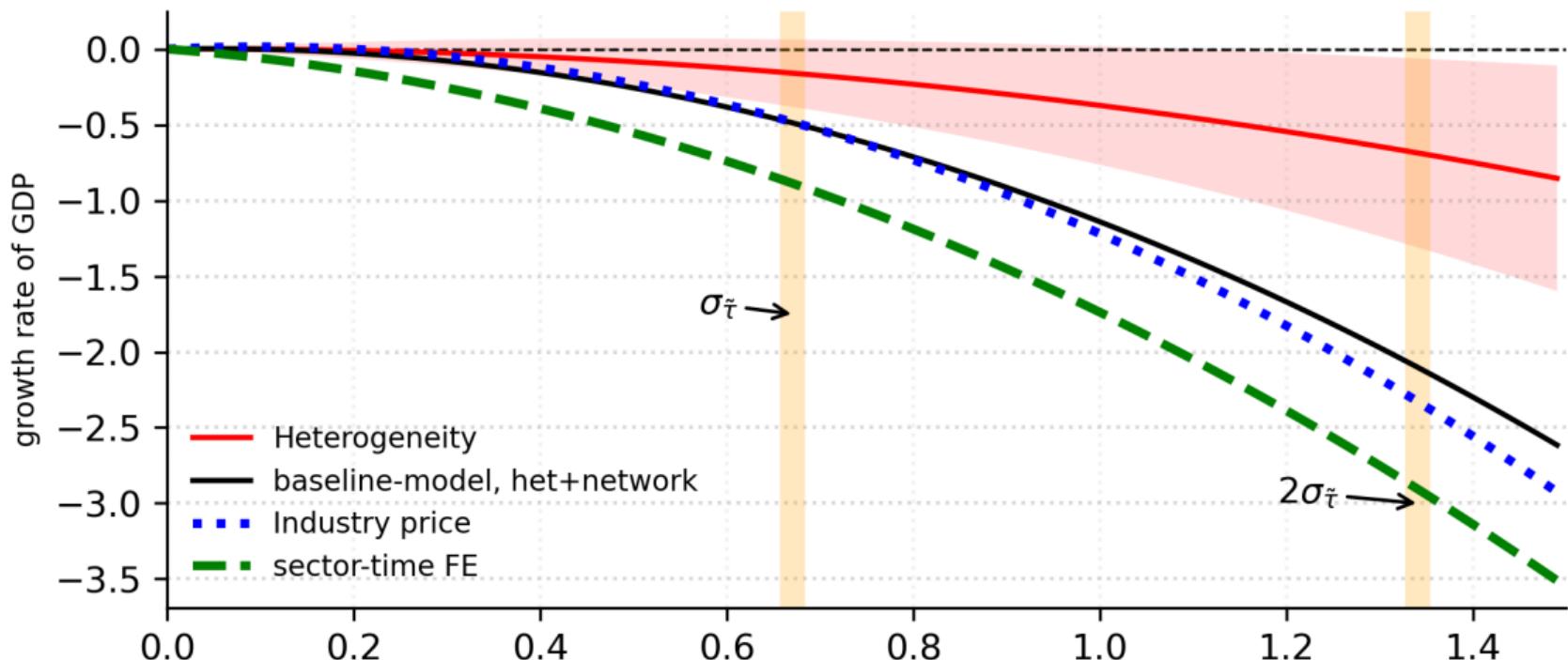
return

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



return

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



return

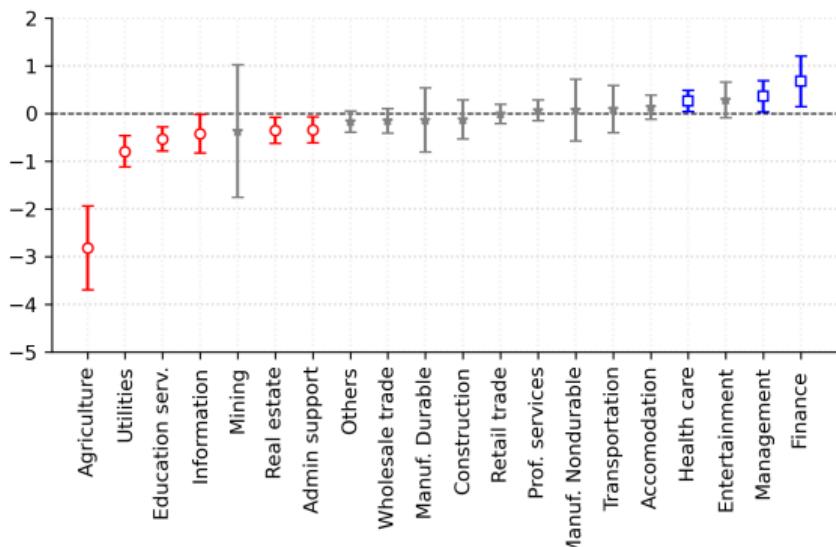
# Additionals

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

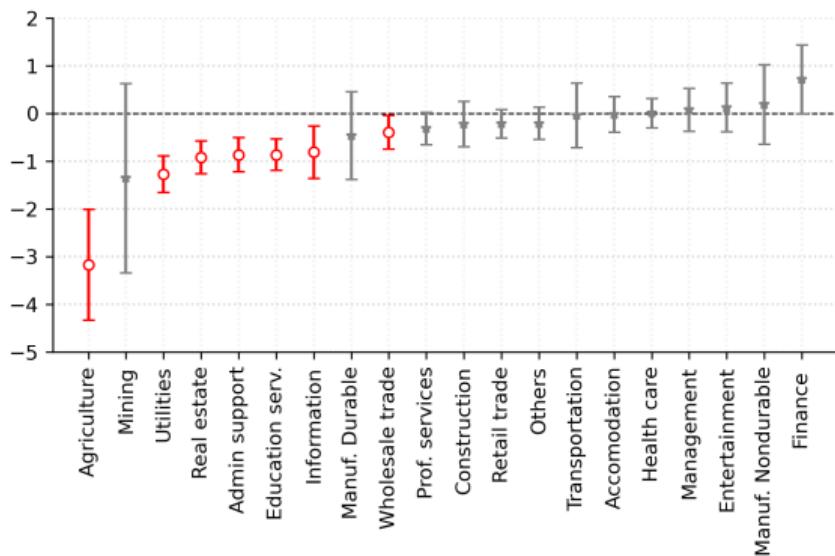
**Industry level:**  $\mathcal{G}_l(\tilde{\tau}_{n,t}^o) = \sum_g w_{ln}^b \mathcal{G}_{ln}(\tilde{\tau}_{n,t}^o),$

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

(a) Small weather shock

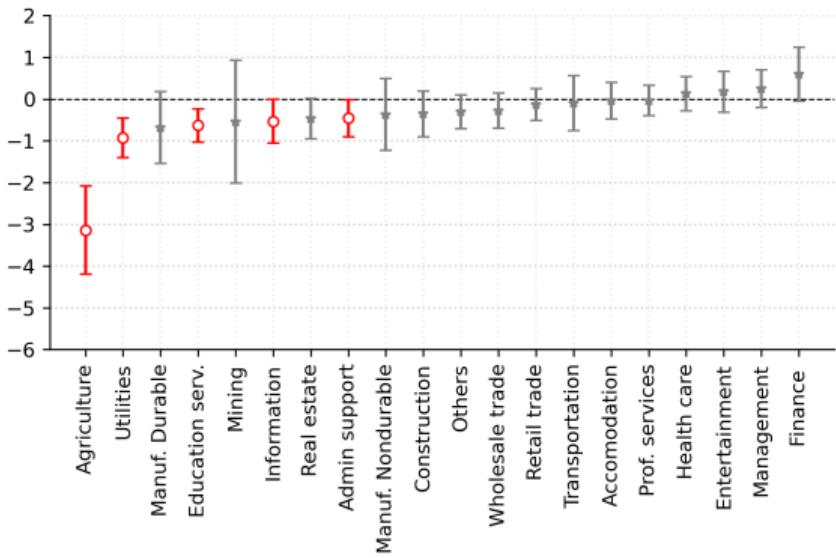


(b) Large weather shock

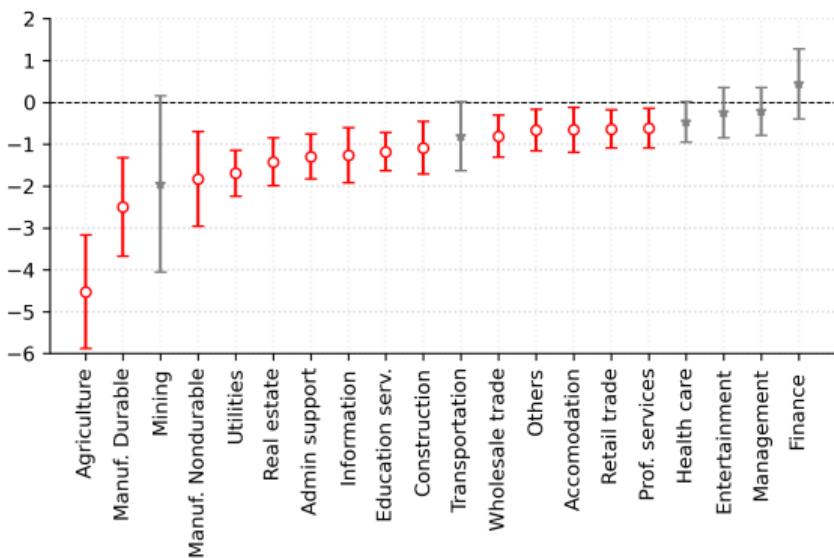


# Impact of $\tilde{\tau}$ by industry: Networks

(a) Small weather shock



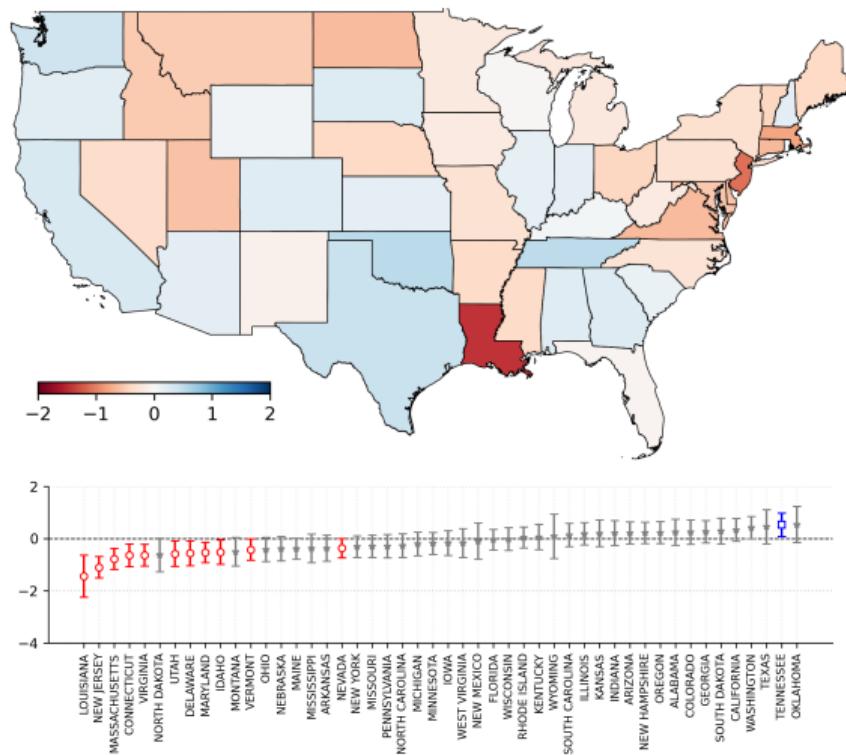
(b) Large weather shock



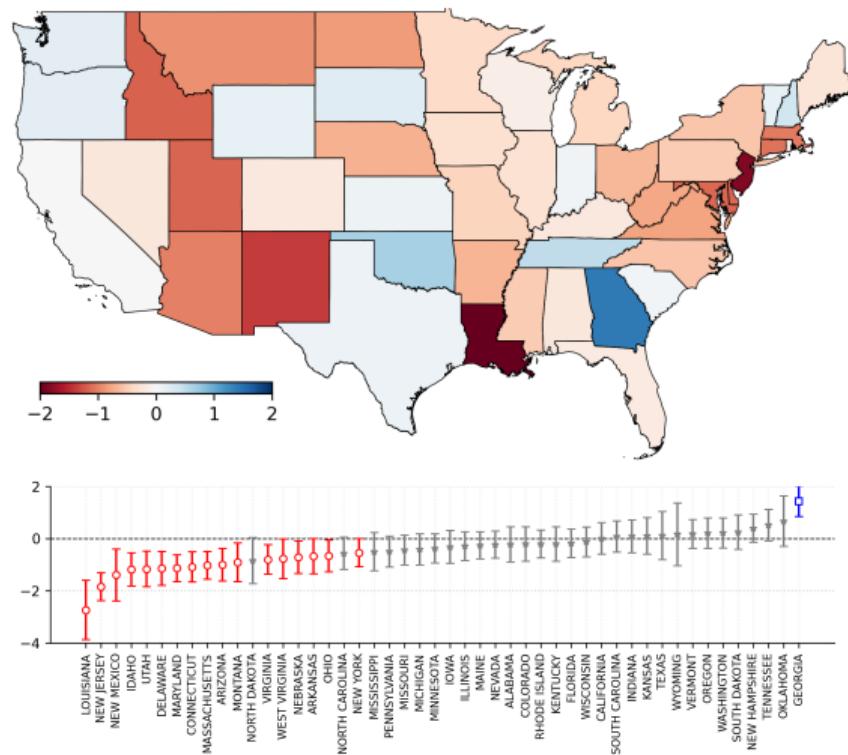
# Impact of $\tilde{\tau}$ at state level

[return](#)

(a) Small weather shock



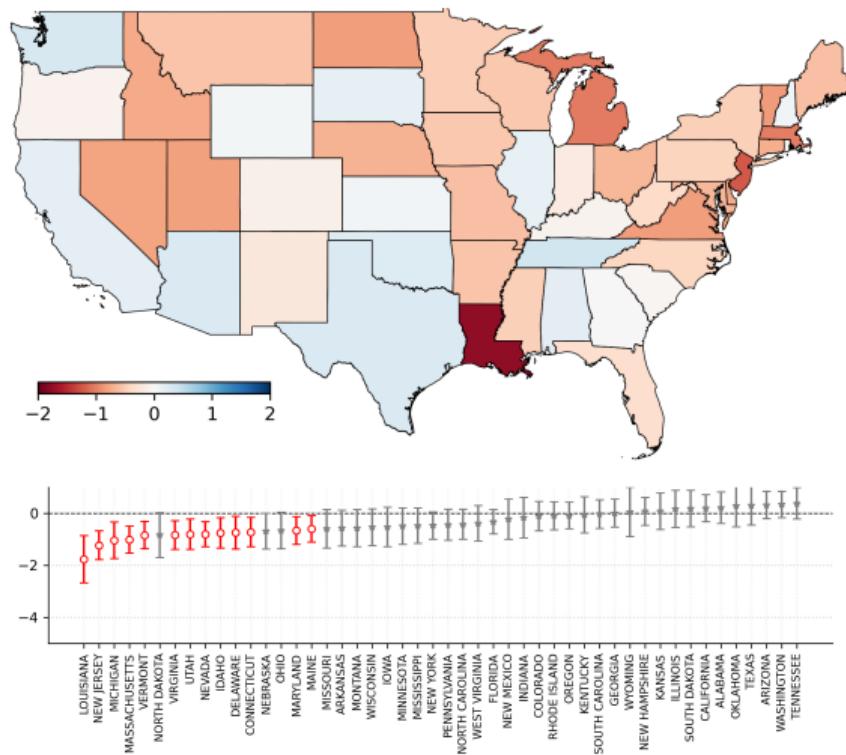
(b) Large weather shock



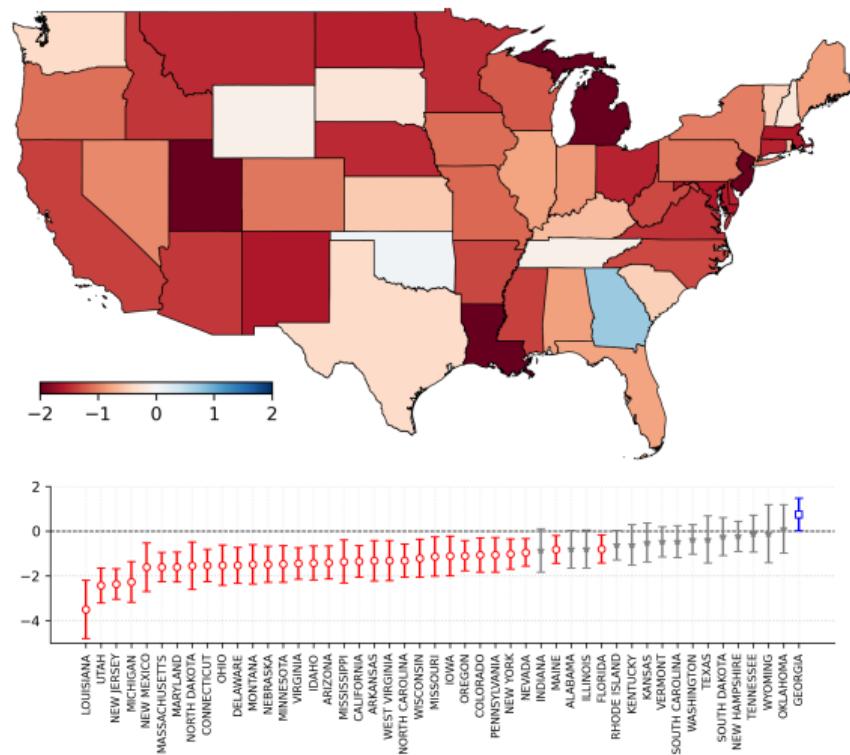
# Impact of $\tilde{\tau}$ at state level

[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:

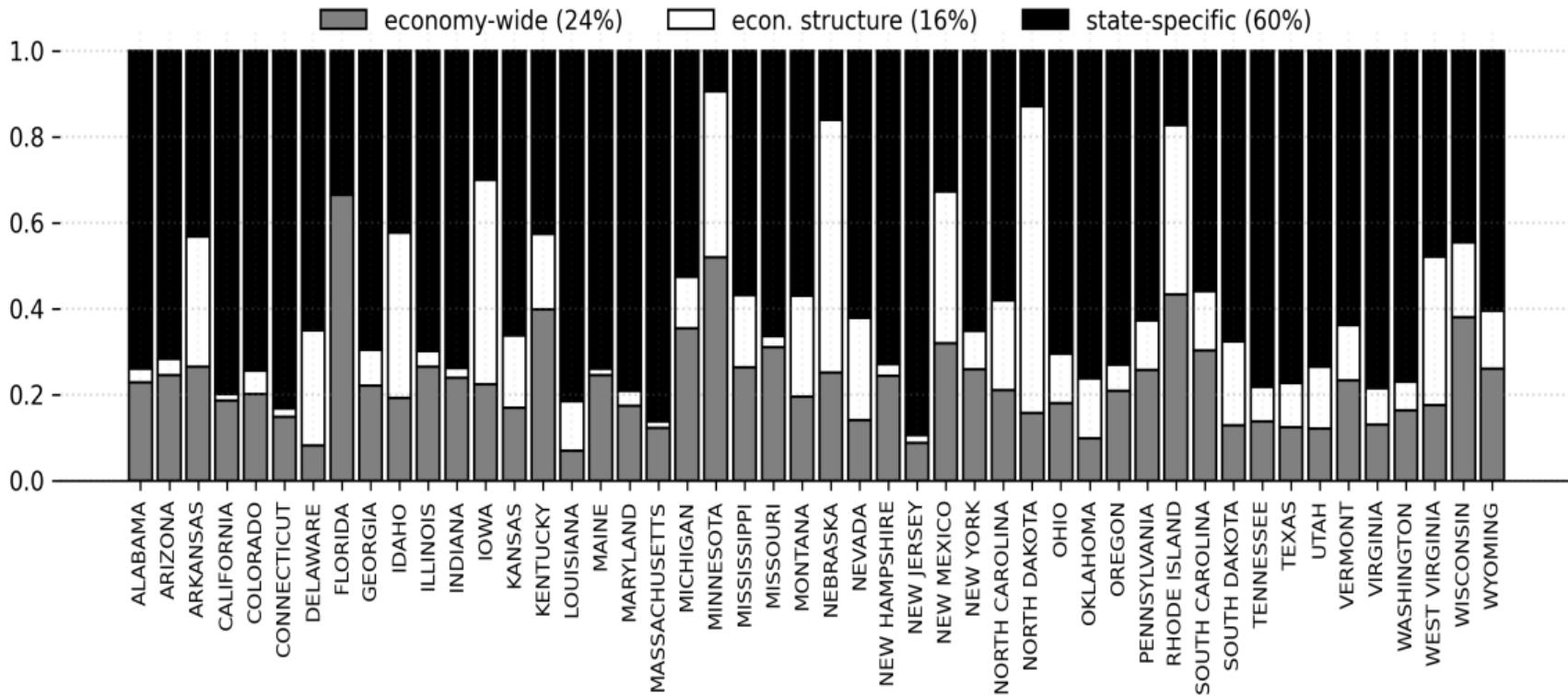
$$\mathcal{A}_{j,i}^{n,m} = \tilde{b}_{,i}^{n,m} \tilde{a}_{ji}$$

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

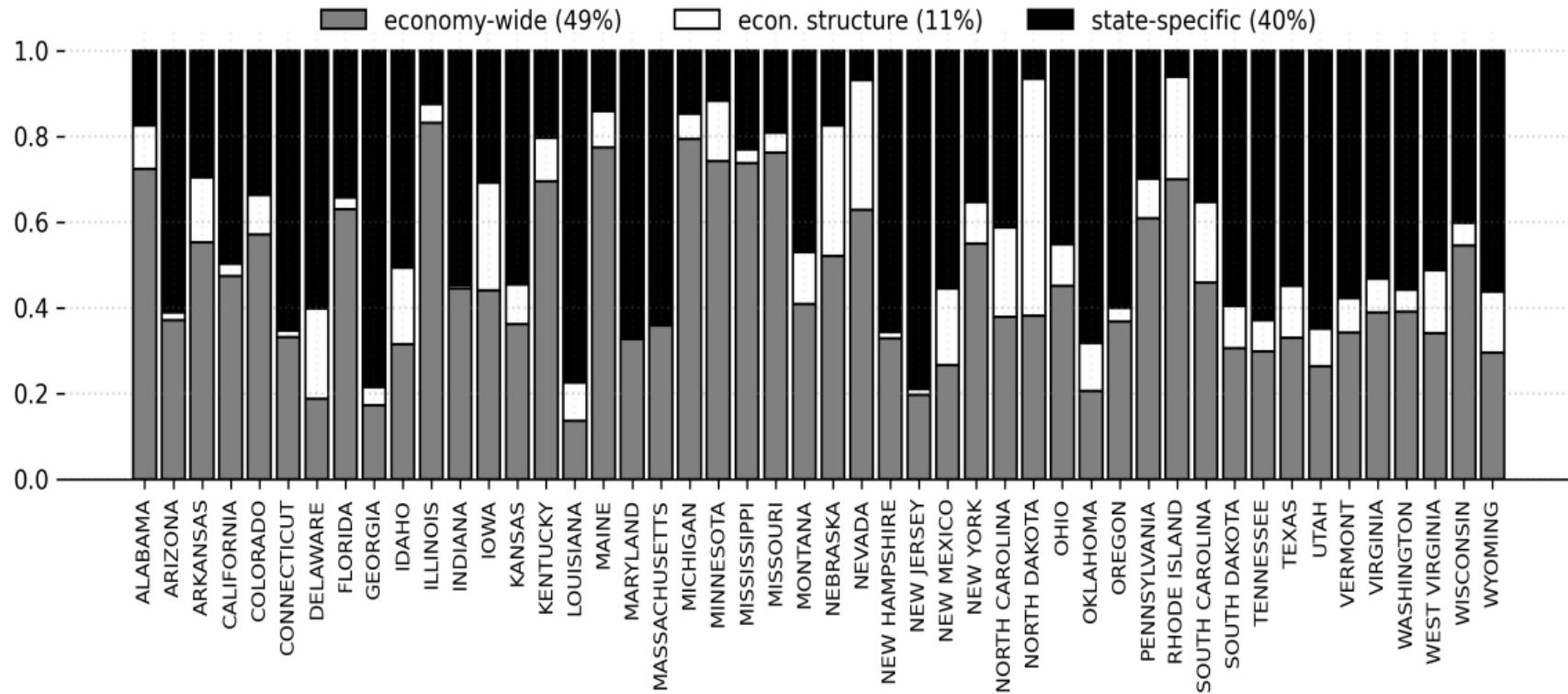
return

# Small weather shock

[return](#)



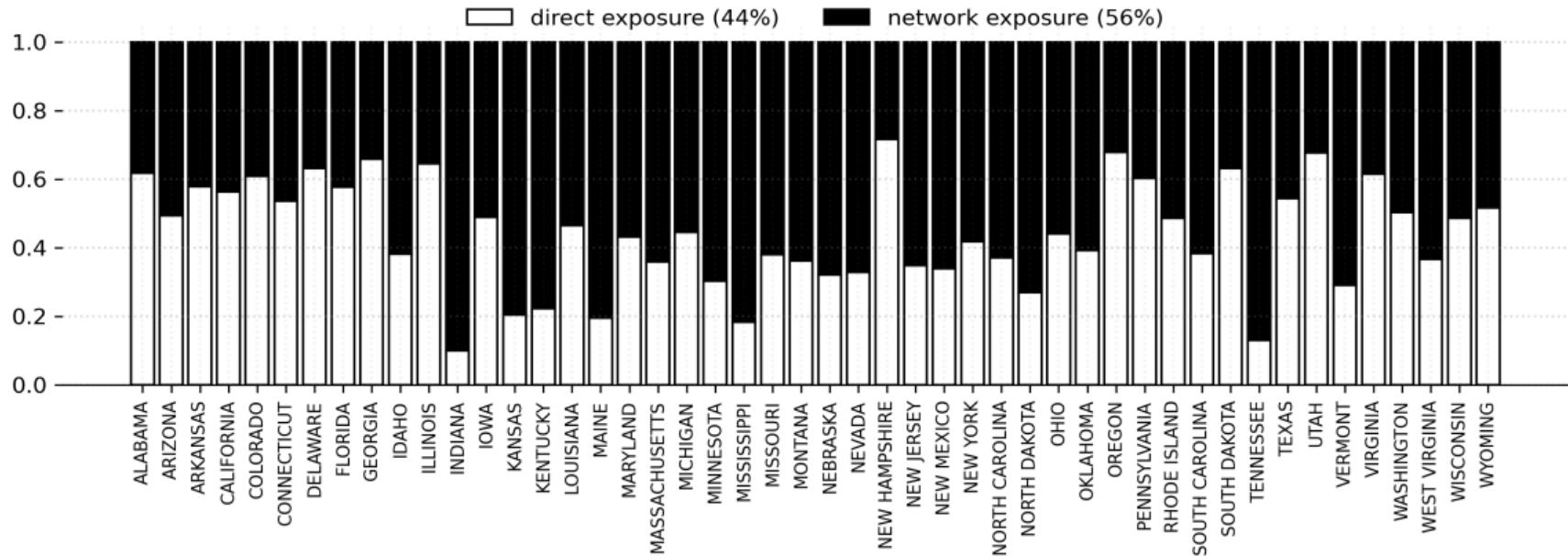
# Large weather shock



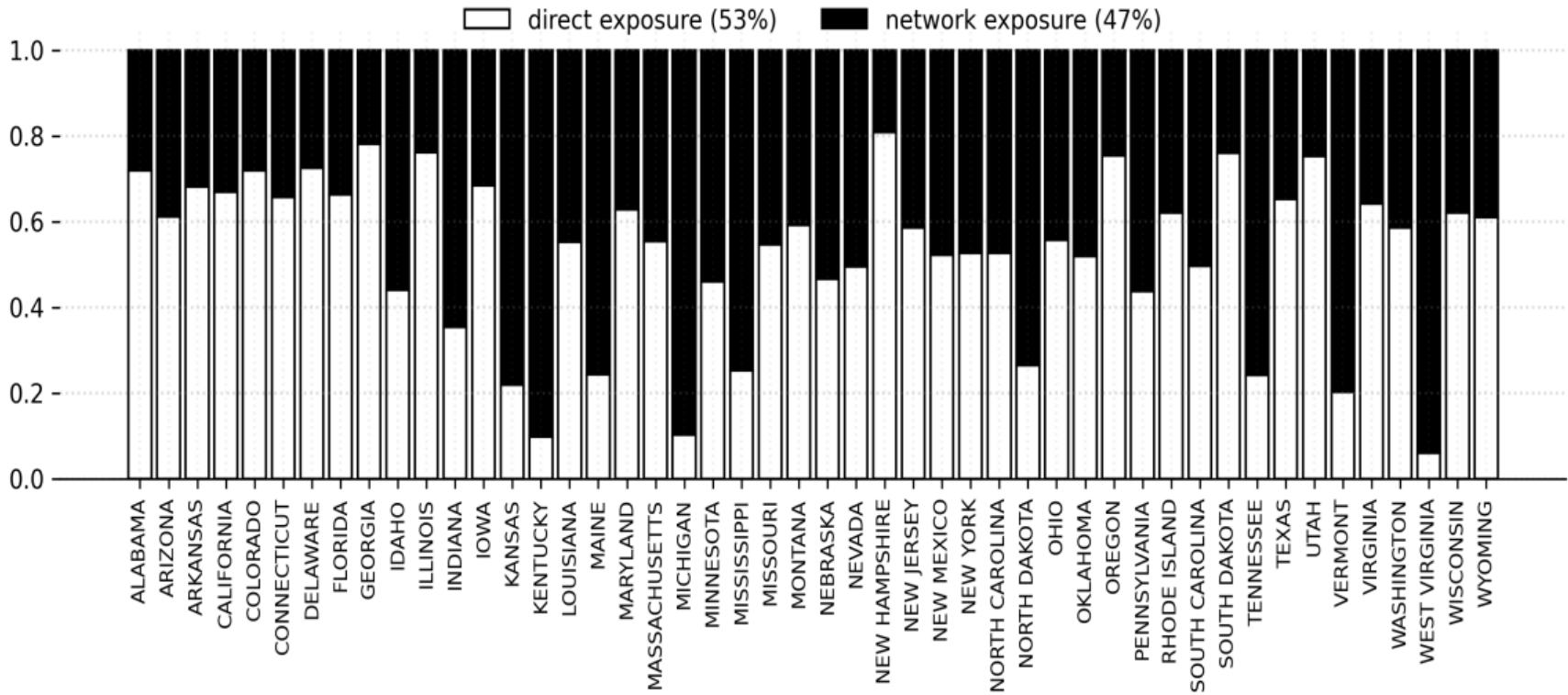
# Direct vs indirect exposure

[return](#)

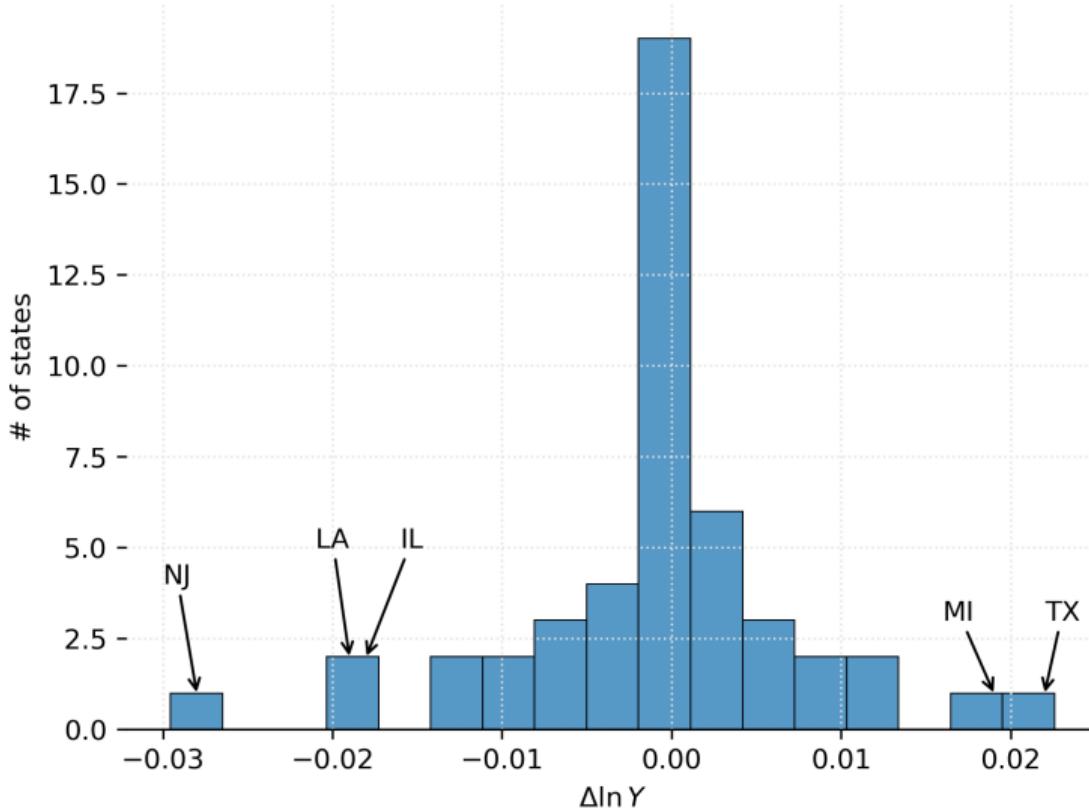
Figure: Small weather shock



## Figure: Large weather shock



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



# References I

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