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 fluctuations on real production**
   - Data on state-sector GDP, weather fluctuations, 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 fluctuations at state level**
   - Local impact is non-linear and heterogenous across states and sectors
   - Differences across states are mostly due to state-specific conditions rather than sectoral composition.
   - Indirect exposure to weather fluctuations through networks amplifies the effect of weather shocks
2. **Aggregate effect of weather fluctuations 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], Gallic 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 Nechio [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:

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

- A representative household with preferences.

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

- 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:

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

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

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

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

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

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

$$d \ln y_n^j \approx (\theta_{n,1} + \theta_{j,1}) \tilde{\tau}_n + (\theta_{n,2} + \theta_{j,2}) \tilde{\tau}_n^2 + \epsilon_{nj} \qquad \text{with } \mathbb{E}[\epsilon_{nj}] = 0 \quad (2)$$

Empirical implementation

The empirical implementation of Equation 2 is:

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

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.
- $\boldsymbol{\theta_n}$ and $\boldsymbol{\theta_j}$ 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)

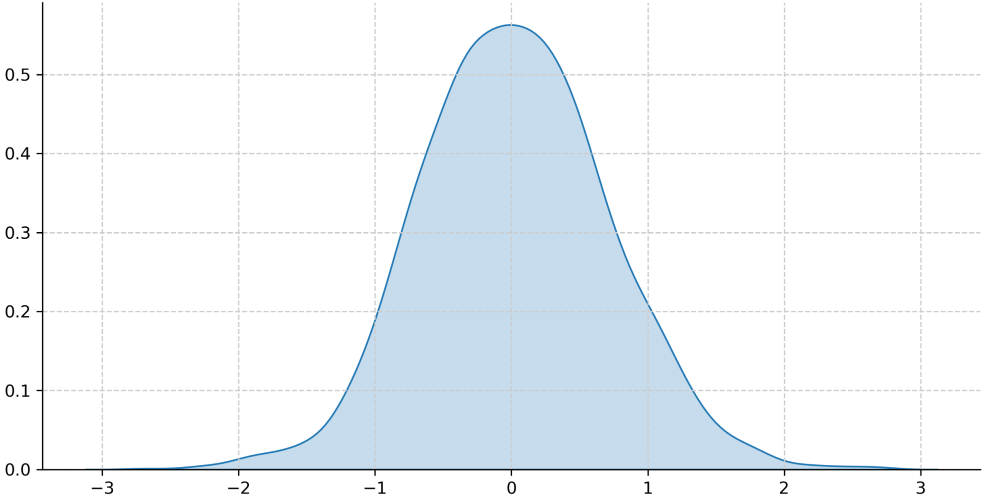
– **Weather fluctuations** ($\tilde{\tau}_{n,t}$):

  - Temperature deviations with respect to a 10-year moving average.

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

– Exogeneity assumption holds due to using deviations instead of levels

Distribution of temperatures deviations



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:

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

- 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)

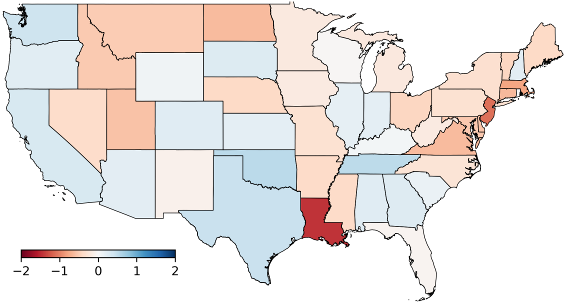
State level: $\mathcal{G}_n(\tilde{\tau}^o_{n,t}) = \sum_j w_{jn}\mathcal{G}_{jn}(\tilde{\tau}^o_{n,t}),$ $\qquad w_{jn} = \frac{1}{T}\sum_t \left(\frac{nom\,GSP_{jn}}{\sum_j nom\,GSP_{jn}}\right)_t$

w_{jn} is the empirical counterpart of b^j_n

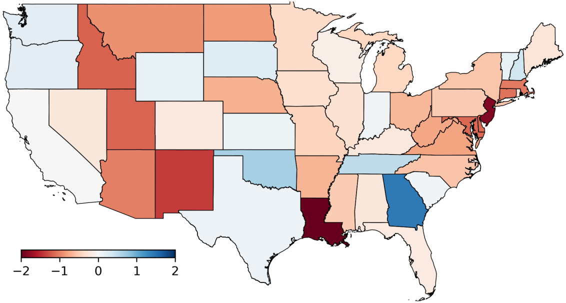
Contemporaneous impact of $\tilde{\tau}$ at state level

confidence

(a) Small weather shock



(b) Large weather shock



Industry level

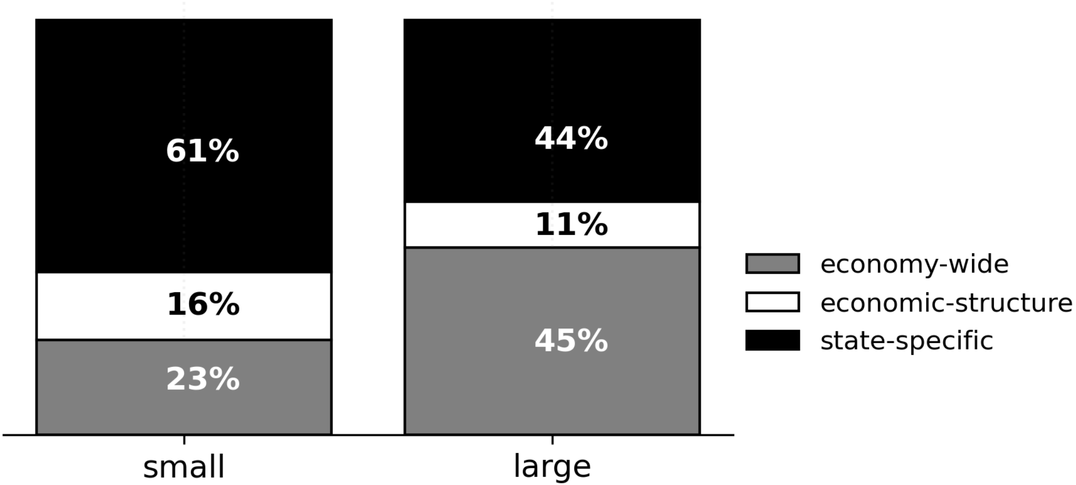
Decomposing $\mathcal{G}_n$

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

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

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

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

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

- Gross output of the state is:

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

- Market clearing condition

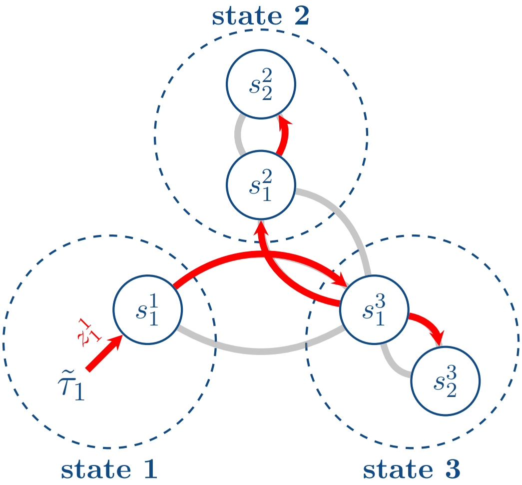
$$q_n = c_n + \sum_{m,j} x_{mn}^j \quad \forall\, n$$

- The solution of this model implies:

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

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:

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

- Aggregation rule

$$\mathrm{d}\ln Y = \sum_{n,j} \beta_n b_n^j d\ln y_n^j \qquad \text{where } \beta_n = \frac{p_n c_n}{PC} \; ; \quad b_n^j = \frac{p_n^j q_n^j}{p_n Q_n} \quad \forall\, n, j \tag{7}$$

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:

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

- $\tilde{\tau}^{network}_{jnt} = \sum_{i,m}\left(\psi_{jn,im} - \mathbf{1}_{jn=im}\right)\tilde{\tau}_{mt}$
  - indirect weather shock through the network connections
- $\tilde{\tau}^{network}_{jnt}$ 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:

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

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:

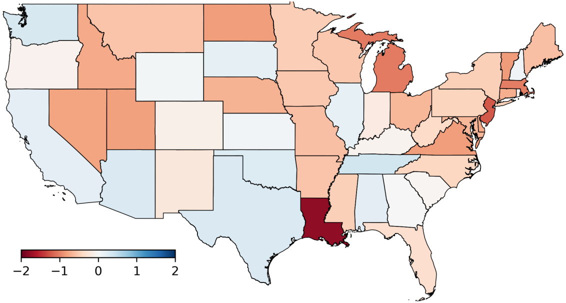
$$\mathcal{G}_n(\tilde{\tau}_{n,t}^o) = \sum_j w_{jn}\mathcal{G}_{jn}(\tilde{\tau}_{n,t}^o)$$

no data on gross output at sector-state level.

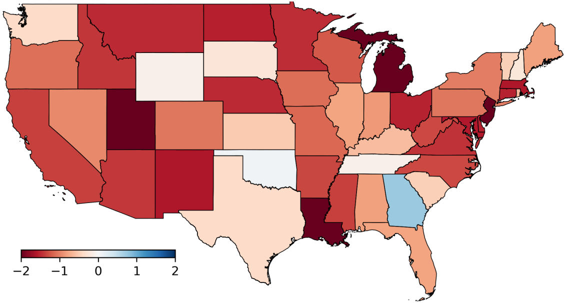
Impact of $\tilde{\tau}$ by state

confidence

(a) Small weather shock

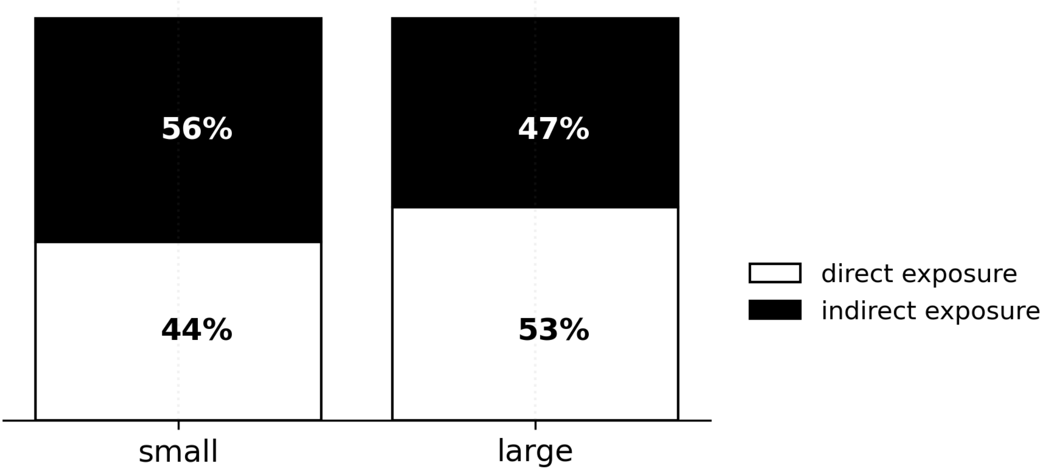


(b) Large weather shock



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

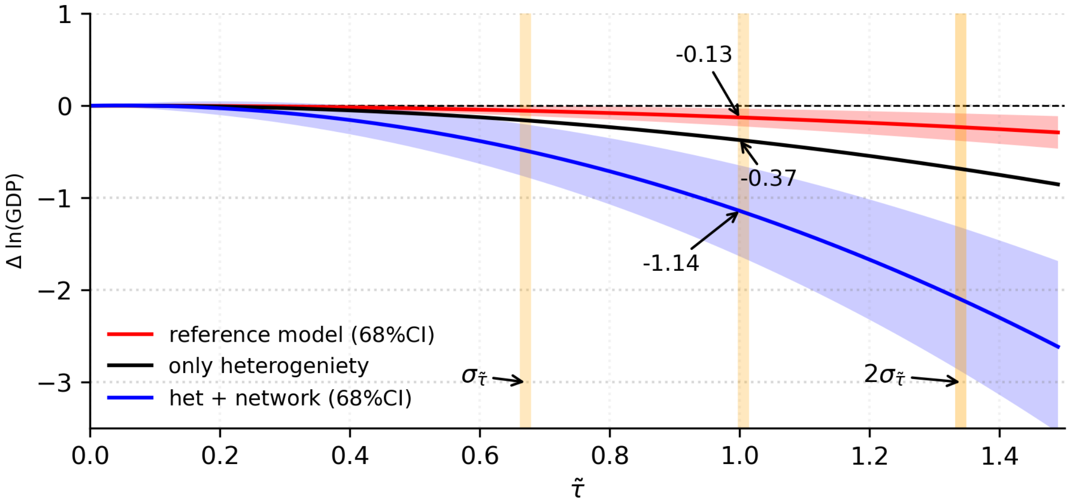
$$\sum_n w_n \mathcal{G}_n^{\text{network}}(\tilde{\tau}^o)\tilde{\tau}^o$$

$w_n = \frac{GDP_n}{\sum_n GDP_n}$ 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 $\tilde{\tau}$

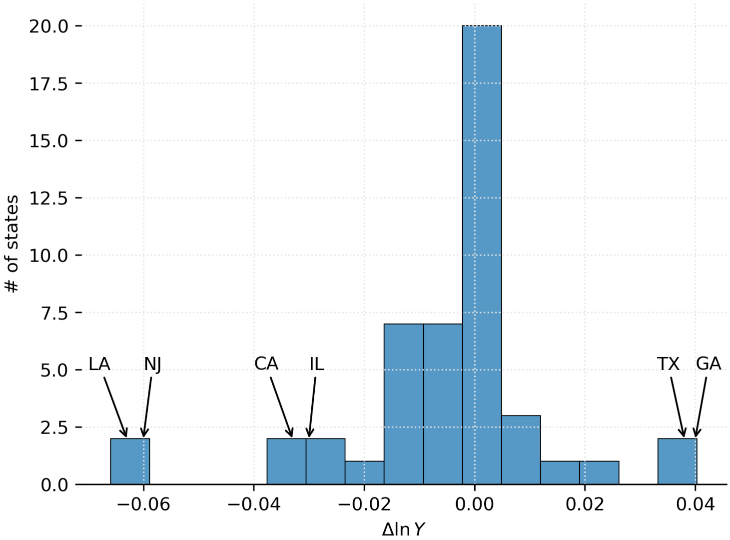


only networks

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 deviations 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 fluctuations 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 deviations 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 deviations

I assume that temperature deviations have underlying common factors

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

I filter the common factors τ_t^k using principal components

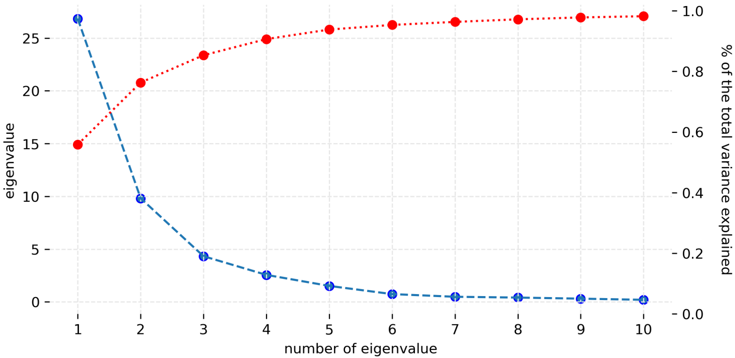


Figure: Factor analysis of weather fluctuations

Geographical distribution of common factors

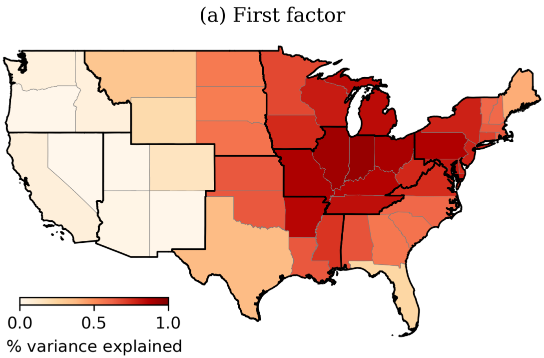
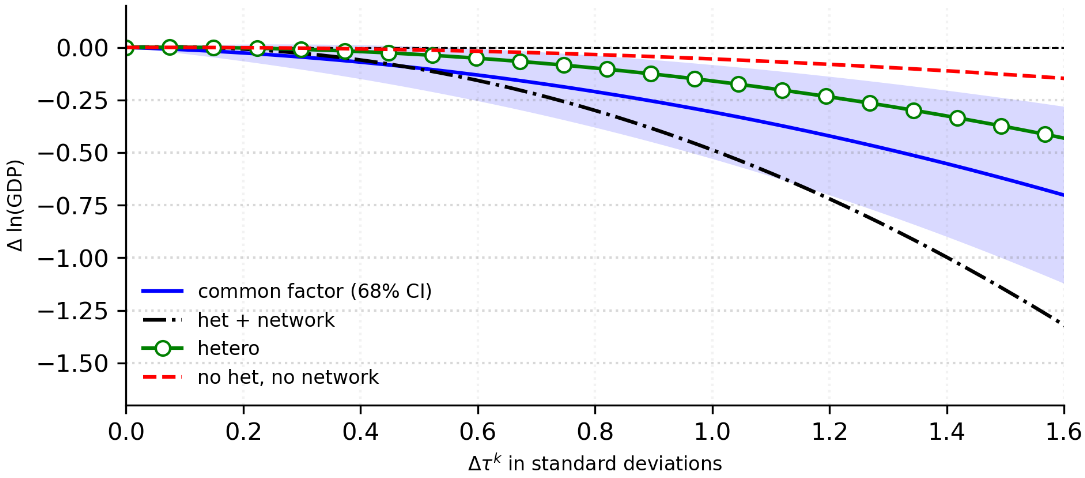


Figure: Contribution to $\sigma^2_{\tilde{\tau}}$ by state

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

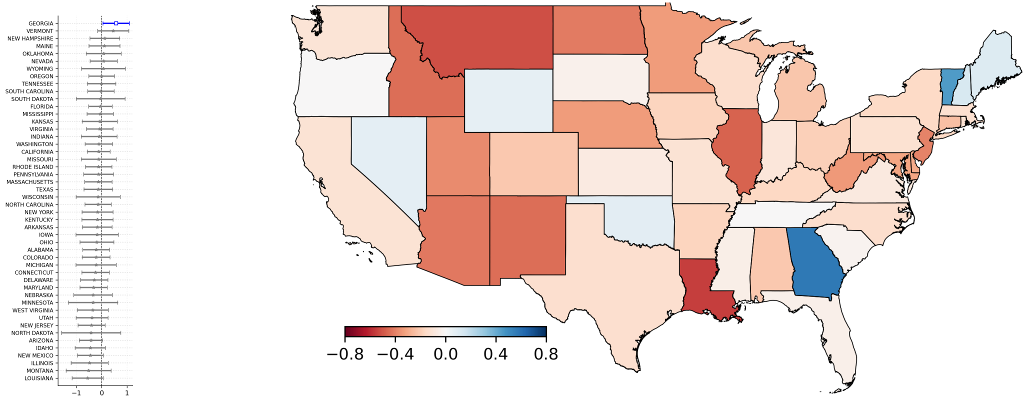


Expected impact of weather fluctuations in the LR

The expected effect of weather variability is: return

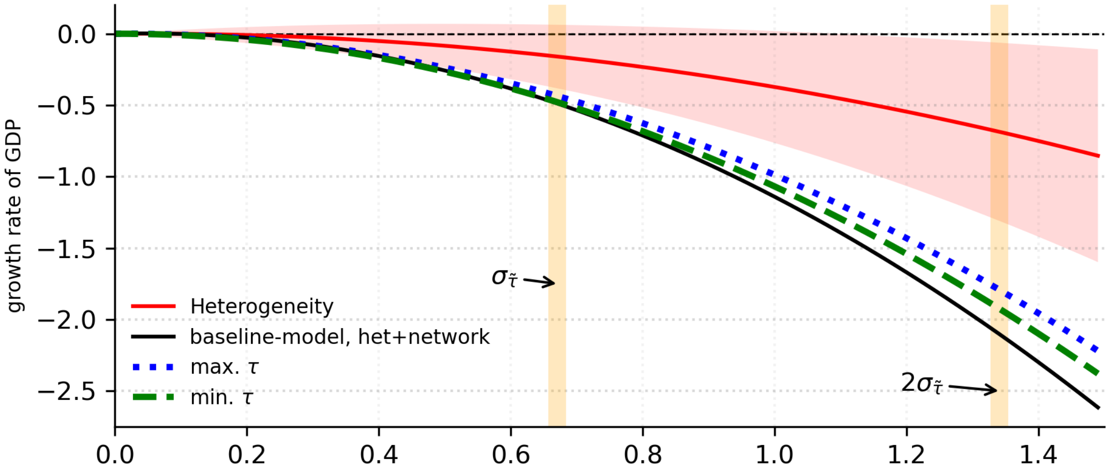
$$\mathcal{H}_{jn} = \mathbb{E}[\Delta y_{jnt}] - \mathbb{E}[\Delta y_{jnt} | \{\tilde{\tau}_{nt} = 0\}_{-\infty}^{\infty}] = \frac{\hat{\delta}_{2n} + \hat{\gamma}_{2j}}{1 - \hat{\rho}_j} \sigma^2_{\tilde{\tau}_n}$$

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



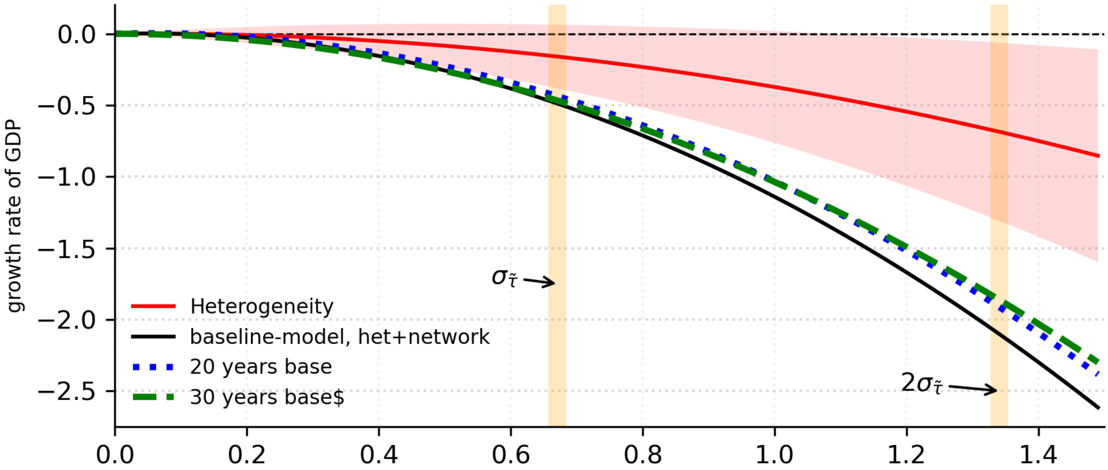
Robustness Analysis

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



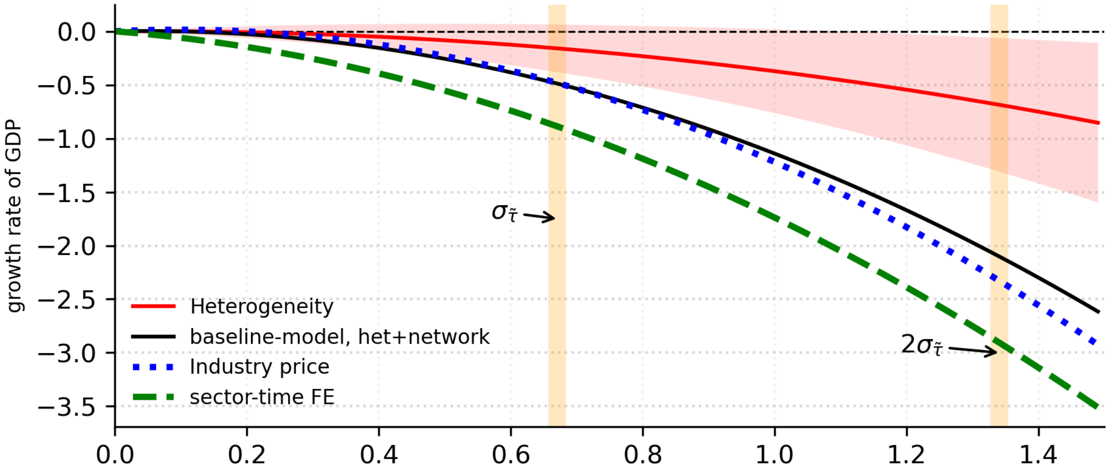
return

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



return

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



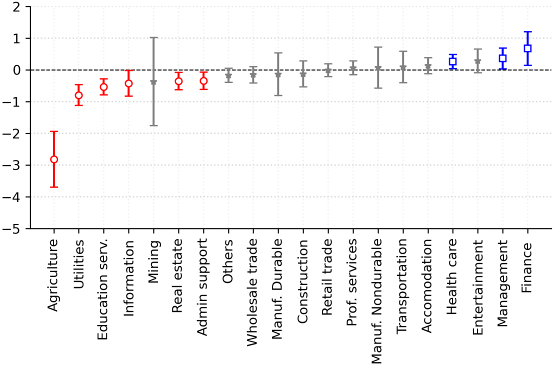
return

Additionals

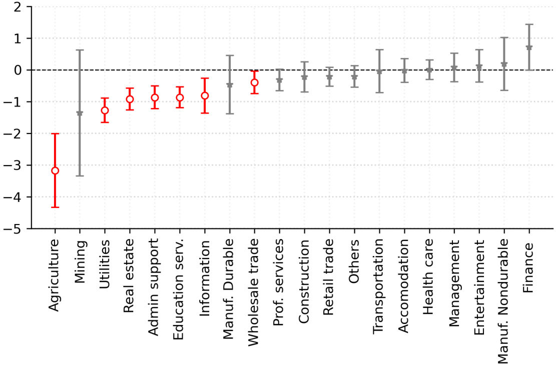
Impact of $\tilde{\tau}$ at industry level

Industry level: $\mathcal{G}_l(\tilde{\tau}^o_{n,t}) = \sum_g w^b_{ln}\mathcal{G}_{ln}(\tilde{\tau}^o_{n,t}),$ $\quad w^b_{ln} = \frac{1}{T}\sum_t \left(\frac{nom, GSP_{ln}}{\sum_g nom\, GSP_{ln}}\right)_t$

(a) Small weather shock



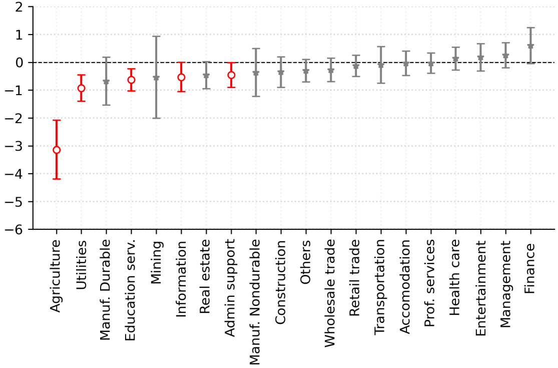
(b) Large weather shock



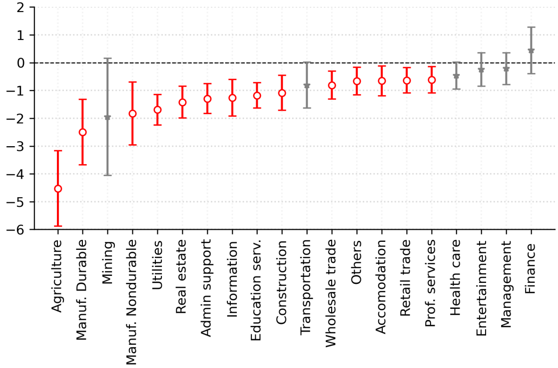
return

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

(a) Small weather shock



(b) Large weather shock

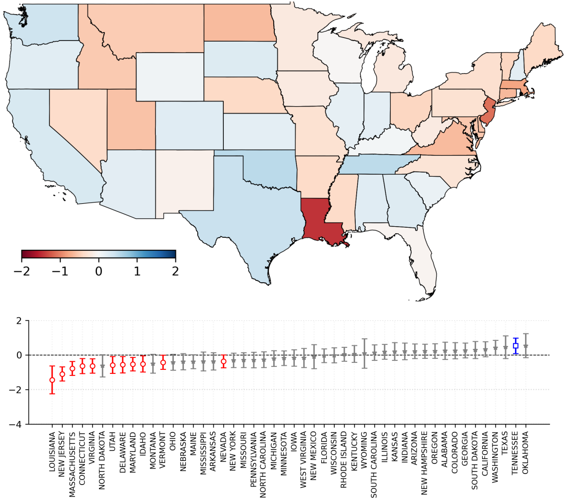


return

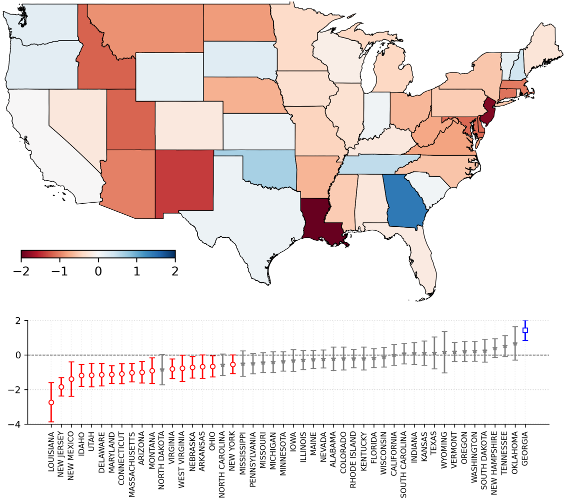
Impact of $\tilde{\tau}$ at state level

return

(a) Small weather shock

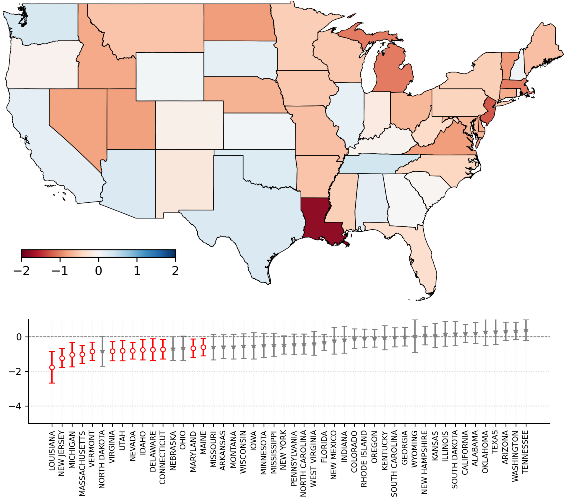


(b) Large weather shock

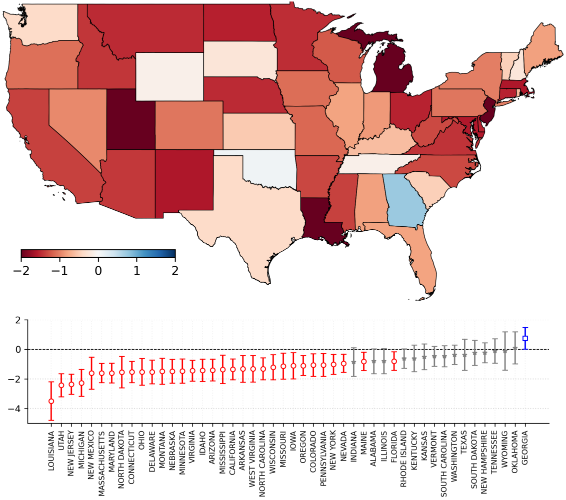


Impact of $\tilde{\tau}$ at state level return

(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:

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

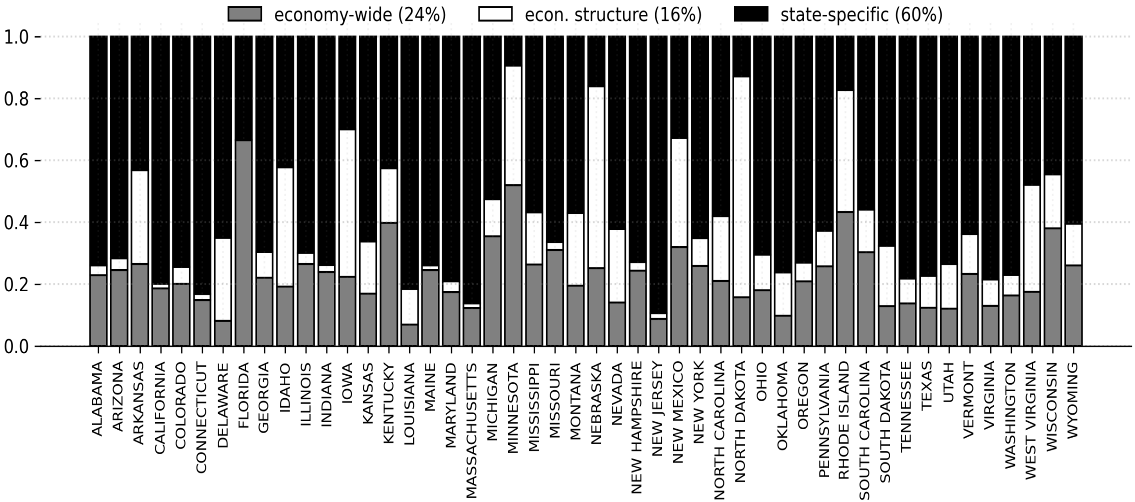
- I approximate the elements of A as:

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

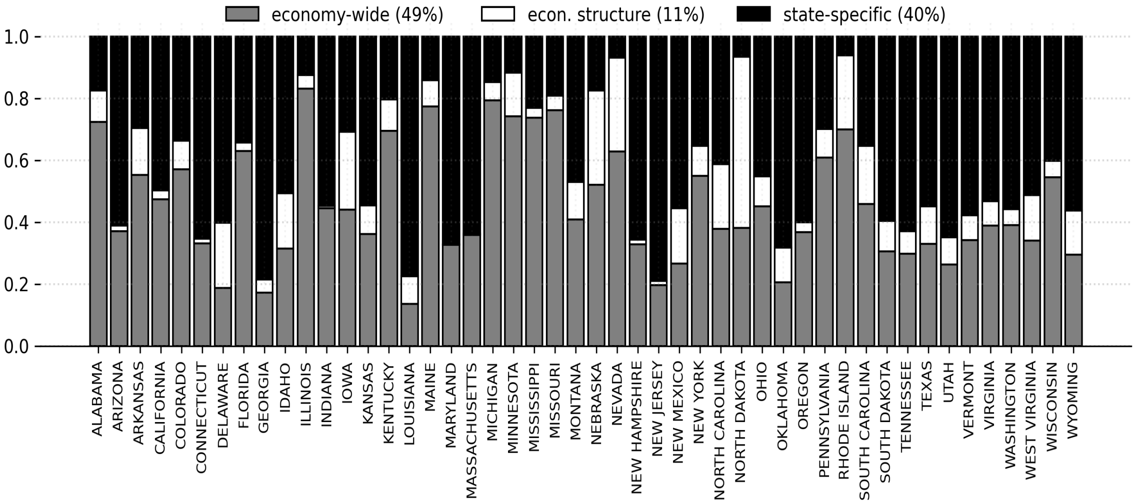
- When the state n buys good i, the fraction used as input is independent of the state from where the product comes

return

Small weather shock return



Large weather shock



Direct vs indirect exposure return

Figure: Small weather shock

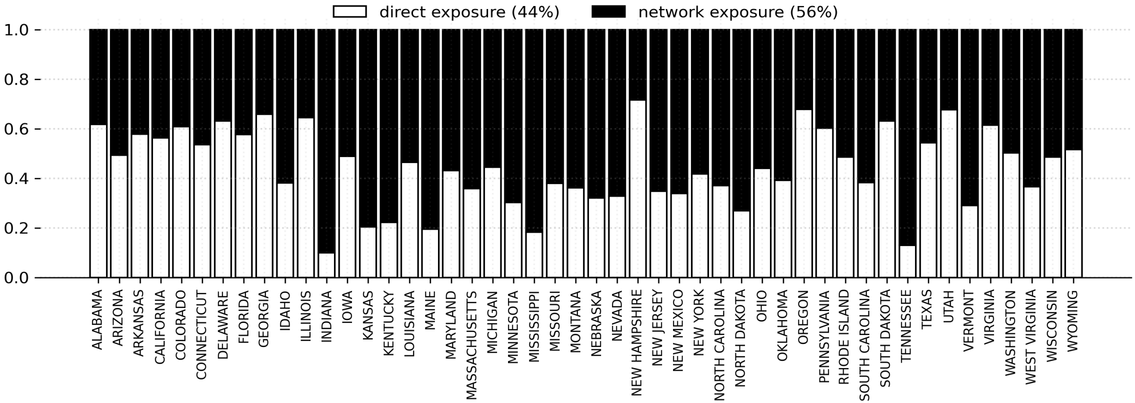
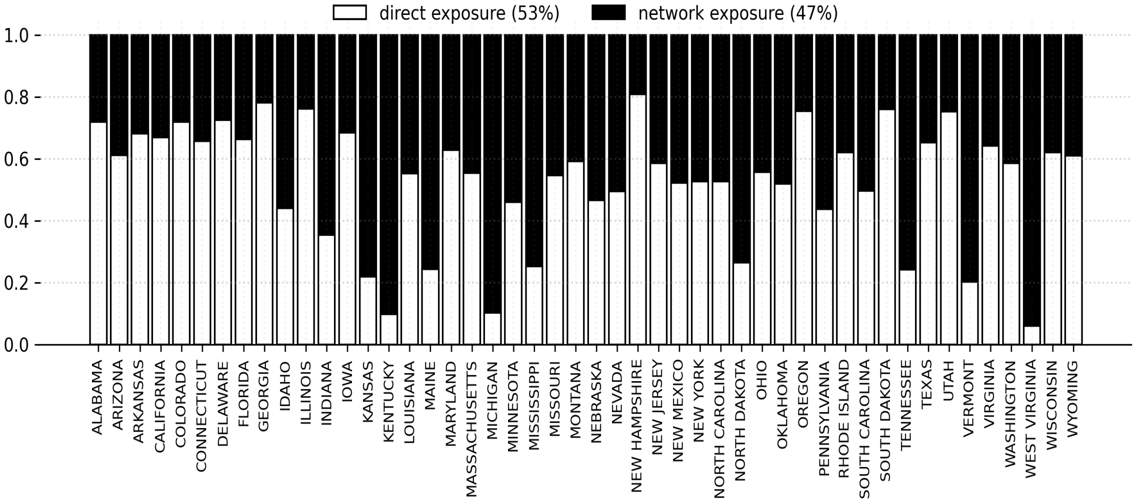
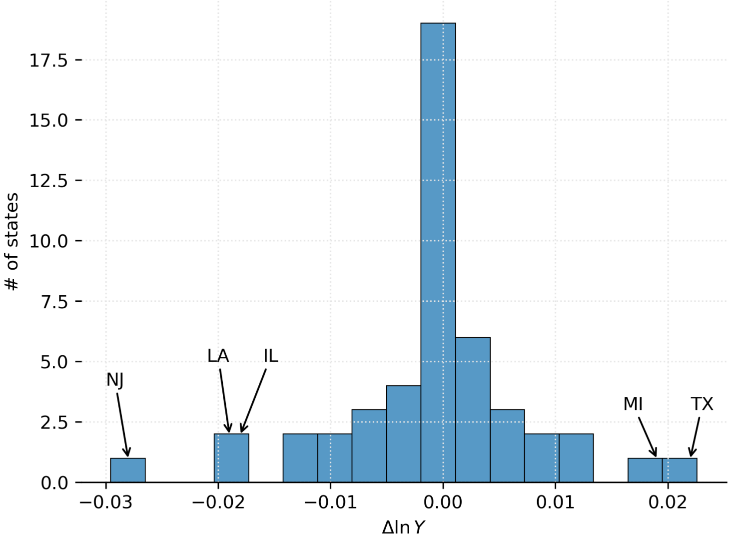


Figure: Large weather shock



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



References I

D. Acemoglu, V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi. The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016, 2012. doi: https://doi.org/10.3982/ECTA9623. URL `https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA9623`.

S. Acevedo, M. Mrkaic, N. Novta, E. Pugacheva, and P. Topalova. The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics*, 65:103207, 2020. ISSN 0164-0704.

J. Barrot, Jean-Noël; Sauvagnat. Input specificity and the propagation of idiosyncratic shocks in production networks *. *The Quarterly Journal of Economics*, 131(3):1543–1592, 2016. ISSN 0033-5533. doi: 10.1093/qje/qjw018. URL `https://browzine.com/articles/59485780`.

A. Bilal and E. Rossi-Hansberg. Anticipating climate change across the united states. Technical report, National Bureau of Economic Research, 2023.

M. Burke, S. M. Hsiang, and E. Miguel. Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239, 2015. ISSN 0028-0836. doi: 10.1038/nature15725. URL `https://browzine.com/articles/56833678`.

L. Caliendo, F. Parro, E. Rossi-Hansberg, and P.-D. Sarte. The impact of regional and sectoral productivity changes on the u.s. economy. *The Review of Economic Studies*, 85(4):2042–2096, 2018. ISSN 0034-6527. doi: 10.1093/restud/rdx082. URL `https://browzine.com/articles/170244898`.

C. Carvalho and F. Nechio. Factor specificity and real rigidities. *Review of Economic Dynamics*, 22:208–222, 2016. ISSN 1094-2025. doi: https://doi.org/10.1016/j.red.2016.08.002. URL `https://www.sciencedirect.com/science/article/pii/S1094202516300242`.

References II

R. Colacito, B. Hoffmann, and T. Phan. Temperature and growth: A panel analysis of the united states. *Journal of Money, Credit and Banking*, 51(2-3):313–368, 2018. ISSN 0022-2879. doi: 10.1111/jmcb.12574. URL `https://browzine.com/articles/250846780`.

M. Dell, B. F. Jones, and B. A. Olken. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95, July 2012.

M. Dell, B. F. Jones, and B. A. Olken. What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3):740–798, 2014. ISSN 0022-0515. doi: 10.1257/jel.52.3.740. URL `https://browzine.com/articles/52775759`.

T. Deryugina and S. M. Hsiang. Does the environment still matter? daily temperature and income in the united states. Working Paper 20750, National Bureau of Economic Research, December 2014. URL `http://www.nber.org/papers/w20750`.

M. Donadelli, M. Jüppner, M. Riedel, and C. Schlag. Temperature shocks and welfare costs. *Journal of Economic Dynamics and Control*, 82:331–355, 2017. ISSN 0165-1889. doi: 10.1016/j.jedc.2017.07.003. URL `https://browzine.com/articles/144467721`.

E. Gallic and G. Vermandel. Weather shocks. *European Economic Review*, 124:103409, 2020. ISSN 0014-2921. doi: https://doi.org/10.1016/j.euroecorev.2020.103409. URL `https://www.sciencedirect.com/science/article/pii/S0014292120300416`.

References III

S. Hsiang. Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of Sciences of the United States of America*, 107:15367–72, 08 2010.

S. Hsiang. Climate econometrics. *Annual Review of Resource Economics*, 8:43–75, 2016.

S. Leduc and D. J. Wilson. Climate change and the geography of the us economy. Technical report, 2023.

I. Rudik, G. Lyn, W. Tan, and A. Ortiz-Bobea. The economic effects of climate change in dynamic spatial equilibrium. 2022.