The Role of Heterogeneity and Production Networks in the Economic Impact of Weather Shocks

Christian Velasquez*

October 2023

Abstract

I study the macroeconomic implications of state and sector specific sensitivity to weather fluctuations and interregional production networks in the United States. I build a general equilibrium model where the impact of weather fluctuations on productivity is state-sector dependent, and networks expose sectors to weather shocks from other regions through the use of intermediate inputs. I use annual data on sectoral GDP and weather by state from 1970 to 2019 to quantify these mechanisms. My estimates show that models that do not consider these characteristics underestimate the aggregate impact of weather fluctuations by at least a factor of 3. In particular, when the whole economy faces an unexpected increase in temperature of 1 Celsius degree, the contraction in economic activity increases from -0.13 to -0.37 percent once heterogeneity is considered and to -1.14 percent when networks are included.

JEL Codes: E23, F18, O13, Q54

Keywords: weather fluctuations, production, climate change, networks, spatial heterogeneity

*Ph.D. Candidate, Boston College. I thank Pablo Guerrón-Quintana, Rosen Valchev, Jaromir Nosal, and Susanto Basu for the extremely valuable discussions and advice. This paper also benefited from long discussions with Diego Ascarza-Mendoza, Alex Carrasco, Arnab Palit, and the workshop participants at Boston College.

1 Introduction

Climate change and global warming have attracted economists and policymakers, prompting efforts to study how they affect the economy. One of the several consequences of these phenomena is the increase in the variability of weather fluctuations. Here, weather refers to short-term realizations of climatological patterns. The impact of such fluctuations can be particularly severe for some regions and sectors while beneficial for others[1] due to the differences in the sensitivity to changes in weather. The impact of these fluctuations extends beyond their local effects, as they propagate throughout the whole economy due to the economic linkages across regions and sectors. Therefore, accounting for these channels is essential to quantify the aggregate effect of weather fluctuations in the economy. In this paper, I study the implications on the United States economic activity, resulting from the heterogeneous sensitivity to weather anomalies across states and sectors and the role played by economic linkages when modeled as production networks.

My analysis starts by building a multi-region and multi-sector general equilibrium model with production networks and regional weather fluctuations. In this economy, sectors within the same region use production from other regions as inputs. Weather fluctuations play a role in the model by directly affecting sectoral production through changes in productivity[2]. These sensitivities are region-sector dependent. Sectors are also exposed indirectly to weather fluctuations from other states by consuming intermediate inputs produced in those regions. The model allows me to obtain an econometric specification that connects weather fluctuations and real GDP growth rates and an aggregation rule that guides my empirical analysis. I implement this exercise using state-level data on sectoral production and temperature anomalies. My results show that neglecting these characteristics underestimates the aggregate effect of weather fluctuations by at least two-thirds and that the additional effect caused by the networks is more critical than the explained by sensitivity heterogeneity. In particular, I show that a sudden increase in temperatures of 1 Celsius degree reduces real gross production by 0.37 percent in the model with only heterogeneous sensitivities. The contraction goes up to 1.14 percent when production networks are included. Omitting both of these channels leads to an estimate of 0.13 percent.

[1] Dell, Jones and Olken (2012), Colacito, Hoffmann and Phan (2018), and Hennessy and Lawrence (2022)

[2] Hancock, Ross and Szalma (2007) shows the negative relationship between task performance and thermal stressors.

To show the presence of heterogeneous sensitivities to weather fluctuations across regions and sectors, I first present a simplified version of my baseline economy without network connections. Following the literature[3], I allow the impact of weather on productivity to be nonlinear. In the empirical implementation, I use annual data for 48 states and 59 sectors from 1970 to 2019. I approximate weather fluctuations with deviations in annual temperature from their average in the last decade. It reduces concerns regarding adaptation and anticipation mechanisms. My results confirm that weather fluctuations impact states and sectors heterogeneously in a nonlinear form. At the state level, an unanticipated small temperature increase of 0.5 standard deviations, around 0.3 Celsius, leads to significant negative responses in 11 states. In contrast, a large temperature shock of 1.5 standard deviations, approximately 1 Celsius degrees, contracts economic activity in 17 states. In both scenarios, Louisiana and New Jersey would be most affected by these shocks. At the industry level, a small temperature fluctuation would reduce the economic activity in agriculture, utilities, and real estate but increase the production in healthcare, management, and finance[4]. In contrast, no industry reacts positively when the economy faces a large weather fluctuation.

Next, I add production networks to measure the role played by inter-regional and inter-sectoral linkages. It introduces two channels that may alter the overall impact of weather fluctuations compared with an economy without connections. First, production networks propagate local fluctuations throughout the economy[5], leading to an indirect exposure to weather fluctuations from other regions. Second, inter-regional outsourcing can attenuate the local impact of local weather fluctuations during times of bad weather. I assume that sectoral production functions are Cobb-Douglas with constant returns to scale. This specification allows me to obtain a well-defined solution where the Leontief inverse matrix summarizes the interactions across regions and sectors. To calibrate these parameters, I use data from the Commodity Flow Survey and the USE table. My estimates show that accounting by production networks increases the negative effects of an unanticipated weather shock common to all states. At the geographic level, 32 out of 48 states show significant negative responses when the economy faces a large shock. In particular, Louisiana (-3.5%), Utah (-2.5%), and New Jersey (-2.3%) are the states most

[3]See for example Burke, Hsiang and Miguel (2015)

[4]These results contrast with Colacito, Hoffmann and Phan (2018) that find positive responses for utilities and mining. The main difference is that my implementation is more flexible and shows that the responses across states are quite different, even for the same sector

[5]Acemoglu et al. (2012), Carvalho (2007), Barrot (2016), Caliendo et al. (2018)

affected by these shocks. At the sectoral level, production of 14 out of 20 sectors reduces, with agriculture (-4.5%), durable manufacturing (-2.5%), and non-durable manufacturing (-2.0%) showing the largest contractions. Moreover, the positive effects on healthcare, management, and finance during small shocks disappear.

When the set of policy instruments is limited, policymakers need to understand whether variations in the impact of weather on GDP at the state-sector level are due to geographical factors or sectoral composition. To address this, I decomposed the state-level effect of temperatures into three components: (i) an economy-wide component, which shows the common effect across the entire economy; (ii) a structure-driven component that measures the fraction of the effect explained by differences between a particular state's economic structure and the average economic structure of the aggregate economy, and (iii) a region-based component that takes into account the unique characteristics of each state. In the absence of networks, around 60 percent of the state-level response is explained by state-specific factors, while 16 percent can be attributed to sectoral composition. Introducing networks generates minimal changes as the state-specific factors and sectoral composition account for 54% and 9% of the response, respectively.

At the macroeconomic level, production networks and heterogeneous sensitivities increase the overall economic impact of weather fluctuations. To show this, I estimate a version of the model without heterogeneous sensitivities to fluctuations and networks. The result from this model suggests that an unexpected increase in temperature of 1 Celsius degree contracts the economy by 0.13 percent. In the model with only heterogeneous sensitivities, a similar increase in temperature reduces the aggregate GDP by 0.37 percent. Including networks amplifies the impact to -1.14 percent. In this case, the direct effect of local weather fluctuations accounts for -0.13 percent of the total impact, and the network effect accounts for -1.01 percent. Similar results are reached from changes in temperatures comprised in the range from 0.01 to 1.5 Celsius degree. The discrepancies between the model with only heterogeneous sensitivities and the direct effect of the second model are explained by the omitted variable bias problem in the former due to the spatial correlation across weather fluctuations. A sensitivity analysis shows that these conclusions are robust to temperature measurements (average, minimum, or maximum), the choice of a reference point (10-year window, 20-year window, or 30-year window), and other specifications.

One potential issue with the previous results is the small likelihood of a temperature rise equal for all regions. To handle this concern, I perform a second counterfactual analysis, where changes in common factors and idiosyncratic movements explain regional weather fluctuations. Then, I feed each common factor by the same shock (in standard deviations) and compute the new aggregate impact. Using a principal component analysis, I show that two common factors contribute to around 80% of the overall weather fluctuations variance. These common factors are associated with the weather conditions of the eastern and western regions, respectively. My estimates suggest that when a shock of 1.5 standard deviations hits both common factors, the contraction of the overall economy is close to 0.62 percent.

The rest of the paper is organized as follows: Section 2 provides a brief review of the relevant literature. In Section 3, the simplified version of the model is introduced and its results are presented. Section 4 presents the main model and its implications at both the state and sectoral levels. Section 5 discusses the macroeconomic implications of both models. Section 6 shows the common factor analysis and its results, and finally, Section 7 concludes the paper.

2 Related Literature

This paper is related to two branches of literature. The first one uses econometric models, exploiting either geographical or sectoral differences to gauge the economic impact of climate change and weather variations in the United States. Previous research has shown that climate change's effect differs across various regions and economic activities. Dell, Jones and Olken (2012), using annual data from 1950 to 2003, find that temperature fluctuations decrease the average growth rate of "poorer nations" by 1.3 percent per Celsius degree but have an almost negligible effect on "wealthier nations". The authors suggest this is due to better adaptation mechanisms in wealthier countries. This result aligns with early macro-estimations that did not find a statistically significant effect of temperatures on the United States' economic activity. However, other researchers have found that higher temperatures significantly negatively affect the United States. For example, Burke, Hsiang and Miguel (2015) conducted a differences-in-differences analysis using income per capita and daily temperature data at the county level in the United States. They categorized daily temperatures into groups, each impacting economic activity differently. They found higher temperatures reduce productivity by around 1.7% per Celsius degree. Moreover, these estimates are not homogenous across geographies or economic sectors. Hsiang et al. (2017), using multiple models, show that the effect of climate change on the

United States differs between the north and south regions. On the sectoral dimension, Acevedo et al. (2020) show that higher temperatures in the summer cause a contraction in the gross product of agriculture (-2.20% per Celsius degree), construction (-0.38%), and services (-0.21%) while many other sectors report no statistically-significant response. Based on these estimates, nonlinearities and heterogeneity are crucial to accurately quantifying how temperature fluctuations affect economic activity. Although previous papers have addressed nonlinearities and heterogeneous effects, to my knowledge, my paper is the first to exploit regional and sectoral variation jointly.

It is important to understand the subtle difference between climate and weather. We can understand weather as the realization of temperatures, precipitation, wind, and other variables in a specific geography over days, months, or one year. In contrast, climate would be the average distribution of such patterns over decades. Dell, Jones and Olken (2014) explained that using weather variation instead of climate to identify changes in output sensitivity to temperature is more appropriate since the exogeneity assumption is more likely to hold. However, due to the high persistence of temperature levels, economic agents can anticipate future temperatures. Therefore, my paper uses weather fluctuations rather than levels to mitigate concerns regarding anticipation. I define weather fluctuations as the annual temperature deviations from their short-run trend.

The second strand comprises papers that use general equilibrium models to analyze the impact of climate change and weather variability on economic activity in the United States. For example, Donadelli et al. (2017) built a representative-agent model with recursive preferences and investment adjustment costs. They found that an increase in temperature costs after one year reduces gross domestic output by -0.5 percent. Among the set of GE models, my paper is more related to models that incorporate economic linkages among sectors and regions. Acemoglu et al. (2012), Carvalho and Tahbaz-Salehi (2019), and Carvalho (2007) briefly introduce and discuss how the input-output linkages propagate micro shocks through the economy. These connections are especially strong in the United States, as Barrot (2016) and Caliendo et al. (2018) show. In the context of climate change, some papers have accounted for production networks. The closest one to my research is Rudik et al. (2022). They developed a dynamic spatial equilibrium model with input-output linkages, sector heterogeneity, amenities, labor mobility, and other inefficiencies. They find that climate change would reduce welfare in the United States, with states in the South being negatively affected while states in the North would experience positive effects. In this paper, I show that differences in the response to weather across states are mostly driven by geographical factors rather than sectoral composition, boosting the role of interregional networks. This dimension is missed in their analysis.

There are some caveats in my estimation. First, I do not include no-weather-related migration flows. For example, as mentioned by Bilal and Rossi-Hansberg (2023), migration of rich households can produce a spurious relationship between economic activity and temperature anomalies. However, this type of spurious relationship is more likely when the dependent variable is some measure of private income, and it is less likely in the case of production. In addition, although migration patterns can affect local impacts (Leduc and Wilson (2023)), its role in the macroeconomic impact looks to be small, as pointed out by Bilal and Rossi-Hansberg (2023). Second, my estimations are based on the assumption of a perfect economy with Cobb-Douglas preferences. even this gives me a simple expression to estimate, which is globally accurate in the case of a Cobb-Douglas production function and a good first-order approximation for any constant CES aggregator (Baqaee and Farhi (2019)), their conclusion would be imprecise if the market is inefficient (see Baqaee and Farhi (2020) and Bigio and La'o (2020)), and *a priori*, it is not possible to know the effect of such inefficiencies on my results.

3 The baseline model without interregional connections

In this section, I present a static model where the economy is composed of N geographies, each populated by J sectors that produce intermediate goods and one firm that produces the final good of the region. All of them operate under perfect comp tition. I denote a particular region and its final good by $n \in \{1, \ldots, N\}$ and a particular intermediate sector as $j \in \{1, \dot{;} J\}$. The only factor of production is labor L, which is inelastically supplied by a representative household who can freely move it across regions[6]. The representative household derives utility from the consumption of final goods according to a Cobb-Douglas utility function:

$$U = \prod_n c_n^{\beta_n} \tag{1}$$

where c_n is the consumption level of the final good produced in the region n and β_n is a taste pa ameter. Then, the consumer optimization problem is choosing the set of final goods $\{c_n\}_1^N$ that maximizes 1 subject to the budget constraint $\sum_n p_n c_n = wL$, where w

[6]Although restrictive, while firms are price-takers, the conclusions of this model are still valid for the case with no labor mobility

denotes the nominal wage.

After defining $C = \prod_n c_n^{\beta_n}$ as the measure of real consumption, the equilibrium conditions for the households imply that the share of the final good n in the total expenditure of the consumer expenditure is constant and can be used to infer the taste parameters $\{\beta_n\}_i^N$:

$$\beta_n = \frac{p_n c_n}{PC} = \frac{p_n c_n}{PY} \tag{2}$$

where $P = \left(\prod_n \beta_n^{\beta_n}\right)^{-1} \prod_n (p_n)^{\beta_n}$ is the aggregate consumer price index. In equilibrium, the market clearing conditions imply that aggregate consumption equals aggregate production, and therefore, β_n is not only an expenditure share but also the share of region n in the aggregate nominal GDP (PY).

In each region, the production of intermediate goods y_n^j uses labor l_n^j as unique input but is exposed to a stochastic productivity shifter zn^j. These intermediate goods can be sold only to the final good producer n, which combines them using a constant return to scale Cobb-Douglas production tec nology. I assume the following functional forms for each of these sectors and final producers:

$$y_n^j = z_n^j(\tilde{\tau}_n)\left(l_n^j\right)^{\alpha_n} \tag{3}$$

$$Y_n = \prod_j \left(y_n^j\right)^{b_n^j} \tag{4}$$

where $\sum_j b_n^j = 1 \,\forall\, n$. As usual in the literature, I assume that the productivity shifter $z_n^j(\tilde{\tau}_n)$ is driven partially by fluctuations in weather conditions of the region n denoted as $\tilde{\tau}_n$ and that such fluctuations are exogenous to the economic activity in the short-run.

For the final-good producer, the optimality condition $b_n^j = \frac{p_n^j y_n^j}{p_n Y_n}$ implies that the production elasticity b_n^j can be inferred from the data as the share of the sector j in the nominal GDP of the reg on n. Moreover, the price index of the region n equals $p_n = \prod_j \left(b_n^j\right)^{-b_n^j} \prod_j \left(p_n^j\right)^{b_n^j}$, leading to the following decomposition:

$$d \ln p_n = \sum_j b_n^j d \ln p_n^j \tag{5}$$

Combining the labor demand function $l_n^j = \alpha_n^j \frac{p_n^j y_n^j}{w}$ with the production function of y_n^j and assuming constant returns to the scale allows us to express the fluctuations in prices as a function of changes in productivity and changes in nominal wages

$$d \ln p_n^j = -d \ln z_n^j(\tilde{\tau}_n) - d \ln w$$

Taking into consideration that the share of total sales of the sector j in the aggregate nominal GDP is constant and equal to $\beta_n b_n^j$ and using the nominal GDP as numeraire ($d \ln w = 0$) allows us to express the fluctuations of real production as a function of changes in the weather conditions:

$$d \ln y_n^j = \frac{\partial \ln z_n^j(\tilde{\tau}_n)}{\partial \tilde{\tau}_n} d\tilde{\tau}_n = f(\tilde{\tau}_n) \tag{6}$$

Following Burke, Hsiang and Miguel (2015), I consider a nonlinear relationship between productivity and weather conditions. It can be easily achieved by making a second-order approximation of 6 on $\tilde{\tau}$. This approximation is: $f(\tilde{\tau}_n) = \theta_{n1}^j \tilde{\tau}_n + \theta_{n2}^j (\tilde{\tau}_n)^2$, where each of the parameters $\theta_{n\ell}^j$ with $\ell = \{1, 2\}$ can be expressed as the sum of a regional component $\theta_{n\ell}$, a deviation $\tilde{\theta}_{n\ell}^j$. Assuming that the expected value of this deviation is zero for all regions and sectors entails the following expression:

$$d \ln y_n^j = (\theta_{n,1} + \theta_{j,1})\tilde{\tau}_n + (\theta_{n,2} + \theta_{j,2})\tilde{\tau}_n^2 + \epsilon_{nj} \qquad \mathbb{E}[\epsilon_{nj}] = 0 \tag{7}$$

Equation 7 gives me a theoretical regression that I can implement to quantify the direct impact of weather anomalies on the economic activity of the sector-state (j, n). Additionally, combining equations 1 and 4 with the market clearing conditions gives us the following expression for the fluctuations of aggregate production.

$$d \ln Y = \sum_{n,j} \beta_n b_n^j d \ln y_n^j \tag{8}$$

implying that I can use the shares $\{\beta_n\}_n^N$ and $\{b_n^j\}_{n,j}^{N,J}$ as weighs to aggregate the impact of weather shock on y_n^j.

3.1 Empirical implementation

In this subsection, I test whether actual data supports that short-run fluctuations in weather impact heterogeneously across regions and sectors. To examine these relationships, I employ data from the national accounts and conduct nonlinear panel data regressions. The Bureau of Economic Analysis (BEA) provides statistics by various levels of geographical and industry disaggregations. While annual data of production by sector at the county and Metropolitan Statistical Areas level is available from 2001, state-level information is accessible from as early as 1963. Since the persistent nature of the climate conditions, I opted to approximate the regional dimension with state-level data to cover the largest possible horizon.

For this analysis, I use real gross state product per capita by sector (GSPpc) as the measure of economic activity. The real GSP is obtained by deflating the nominal GSP with state-specific consumer prices. In 1997, the BEA changed the classification system from the Standard Industrial Classification (SIC) to the North American Industrial Classification System (NAICS), which generated a break in the time series. To handle this problem, I use the weights from Yuskavage et al. (2007) to chain both systems. Consumer price indexes were obtained from the Bureau of Labor Statistics. Their data reports price indexes for 21 MSAs and four regions. After that, the dataset is composed of annual information from 1970 to 2019 from about 48 states and 59 sectors that can be aggregated into 20 industries. A more detailed explanation of the data processing can be found in appendix A

I use short-run temperature fluctuations as a proxy for weather shocks. Although weather is a complex concept considering variables such as temperature, wind, precipitation, moisture, and others, I follow the literature and choose temperature as a proxy for weather. Nevertheless, there are some drawbacks to using it directly in an econometric analysis. Firstly, since the observed increase in global temperatures may be partly attributable to elevated levels of CO2 stemming from human activities, a simple regression can face a reverse-causality problem. Secondly, the high persistence of temperature and climate conditions exacerbates the bias caused by omitting variables that control for any anticipation and adaptation mechanism that economic agents have. To address these sources of inconsistency, I focus my analysis on short-run movements that can be easily assumed as unanticipated and exogenous from human activity. To do so, I use the following formula:

$$\tilde{\tau}_{nt} = \tau_{nt} - \bar{\tau}_{nt} \qquad \bar{\tau}_{nt}\frac{1}{10}\sum_{s=1}^{10}\tau_{nt-s} \tag{9}$$

where τ_{nt} denotes the average temperature for the state n at year t, and $\bar{\tau}_{nt}$ is the local trend average temperature in the previous 10 years. In this way, $\tilde{\tau}_{nmt}$ captures temperature fluctuations relative to a local trend. While climatological literature often defines temperature anomalies as deviations with respect to a 30-year basis, I chose a ten-year basis for my baseline analysis since many economic decisions with medium and long-run implications, such as investment plans, have an average window of 8-10 years. Before entering into 10, I adjusted $\tilde{\tau}_{nt}$ by subtracting the mean value specific to each state: $\tilde{\tau}^{\text{adjusted}}_{nt} = \tilde{\tau}_{nt} - \frac{1}{T}\sum_t \tilde{\tau}_{nt}$. I follow this approach to mitigate any bias caused by possible anticipation of the mean by economic agents. After this adjustment and to ease exposition, I refer $\tilde{\tau}^{\text{adjusted}}_{nt}$ simply as $\tilde{\tau}_{nt}$ for the remainder of the paper. Then, I run the following regression:

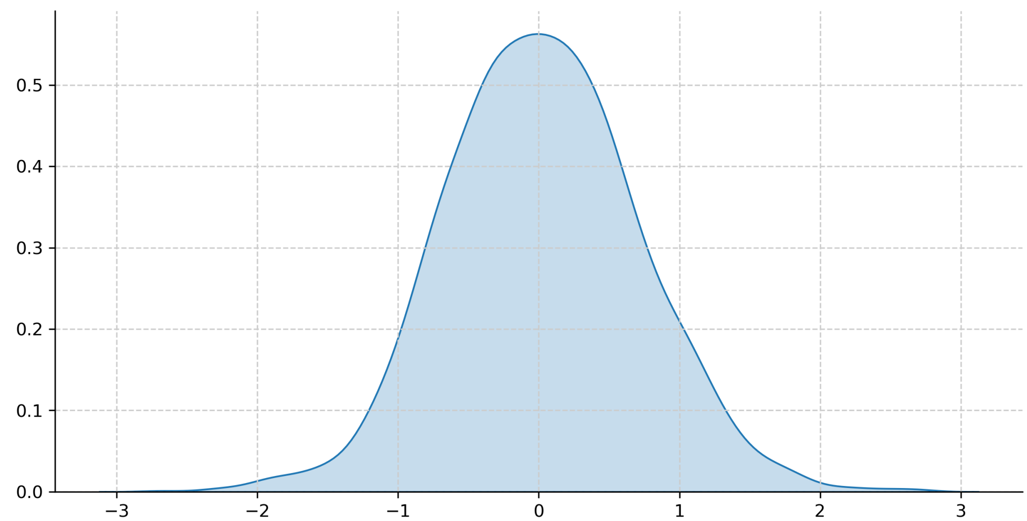
$$\Delta\tilde{y}_{j,n,t} = \alpha + \rho_j \Delta\tilde{y}_{j,n,t-1} + \left(\theta_{n,1} + \theta_{j,1}\right)\tilde{\tau}_{n,t} + \left(\theta_{2,n} + \theta_{j,2}\right)\tilde{\tau}^2_{n,t} + \gamma_j + \gamma_t + \gamma_n + \epsilon_{j,n,t} \tag{10}$$

where $\Delta\tilde{y}_{jnt}$ represents the first log-difference of the real output per capita of the sector j located in the state n during year t, and $\tilde{\tau}_{nt}$ is my measure of weather shocks for state n. This regression incorporates sectoral fixed effects (γ_j), state fixed effects (γ_n), and time fixed effects (γ_t) to control by unobservable components that can explain differences in the growth rates across sectors, states and the effects of business cycles or aggregate shocks. Additionally, the lag of the outcome variable $\Delta y_{jn,t-1}$ is included to account for any persistent dynamics inherent in economic variables. Finally, I avoid considering additional contemporaneous covariates to maintain a parsimonious specification and prevent potential issues arising from bad controlling (Dell, Jones and Olken (2014)).

Equation 10 accommodates nonlinear effects by including the square of the weather shock ($\tilde{\tau}^2_{nt}$). It permits a different impact between small and large shocks. It is motivated by the understanding that small changes in temperature could lead to either beneficial or adverse effects, while in most cases, large changes would have detrimental consequences for the economy. In particular, using a meta-analysis of around 300 experiments, Hancock, Ross and Szalma (2007) show that productivity - measured by task performance- reduces when people face thermal stressors encompassing both elevated temperatures and cold conditions. While numerous functions can capture nonlinear relationships, this particular specification offers some advantages. First, the chosen function is continuously differentiable, enabling an easy computation of results objects such as contemporaneous impacts, marginal effects, and volatility contributions. Second, I can apply the delta method to compute confidence intervals, which improves the efficiency of the estimation. Third, it maintains the parsimonious nature of the model.

In addition, specification 10 examines potential heterogeneities not only across states but also across sectors. This feature acknowledges the inherent complexity of real-world economic activities. Economic sectors could exhibit diverse sensitivities to temperature shocks due to differences in production processes, technology, and exposure.

Figure 1. Distribution of temperature anomalies $\tilde{\tau}$: 1970-2019



Note: Distribution of weather fluctuations $\tilde{\tau}$. Weather anomalies were constructed as the average monthly difference between the observed average temperature at month $\tau_{m,t}$ and the average temperature of the previous 10 years for the similar month $\bar{t} = \frac{1}{10}\sum_{l=1}^{10}\tau_{m,t-l}$. Temperatures are expressed in Celsius degrees.

Moreover, the wide variation of the short-run temperature fluctuations ensures the identification of the parameters $\theta_{n,2}$ and $\theta_{j,2}$, which are associated with the nonlinear effects. This can be confirmed by looking at the histogram displayed in figure 1, which shows the distribution of the observed weather fluctuations $\tilde{\tau}$ during my estimation sample. We can see that large fluctuations are not extreme events. With a standard deviation close to 0.67 Celsius degrees, approximately 15 percent of the observed fluctuations are larger than one Celsius degree in absolute value, while five percent exceed a threshold of 1.4 Celsius degrees.

- Contemporaneous impact of weather fluctuations

A first outcome derived from the aforementioned regression analysis pertains to the expected contemporaneous impact of a weather fluctuation $\tilde{\tau}^0$ on the growth rate of the sector j situated in the state n. I denote this outcome as $\mathcal{G}_{jn}$ and compute it as showed in equation 11[7]. $\mathcal{G}_{jn}$ is standardized per Celsius degree to improve comparability.

$$\mathcal{G}_{jn}(\tilde{\tau}^o_{n,t}) = \mathbb{E}\left[\frac{\Delta y_{j,n,t|\tilde{\tau}_{nt}=\tilde{\tau}^o} - \Delta y_{j,n,t|\tilde{\tau}_{nt}=0}}{\tilde{\tau}^o}\right] = \hat{\theta}_{n,1} + \hat{\theta}_{j,1} + \hat{\theta}_{n,2}\tilde{\tau}^o_{n,t} + \hat{\theta}_{j,2}\tilde{\tau}^o_{n,t} \qquad (11)$$

Figure 2 displays the expected effect per Celsius of a small weather shock (panel 2a) and a large weather shock (panel 2b) as heatmaps. I define a small weather shock as an increase of temperature by 0.5 standard deviations, which is close to the average increase in average temperature by decade in the last 30 years[8] and a large weather shock as 1.5 standard deviations which is around 1 Celsius degree. In each heatmap, the cell positioned at the intersection of row l and column g denotes the contemporaneous impact of a weather shock on the growth rate of the industry j within the state n. These industry results were calculated as the weighted average of the sectoral responses using the share on sectoral GSP as a share of the total GSP as weighs, $\mathcal{G}_{ln}(\tilde{\tau}^o_{n,t}) = \sum_{j\in l} \frac{\sum_t GSP_{jn,t}}{\sum_{j\in l,t} GSP_{jn,t}} * \mathcal{G}_{jn}(\tilde{\tau}^o_{n,t})$. Shades of blue denote positive impacts, while hues of red are associated with negative ones. Furthermore, as in any heatmap, the intensity of the color is linked to the magnitude of the impact, with larger responses, regardless of the sign, being depicted with more saturated colors.

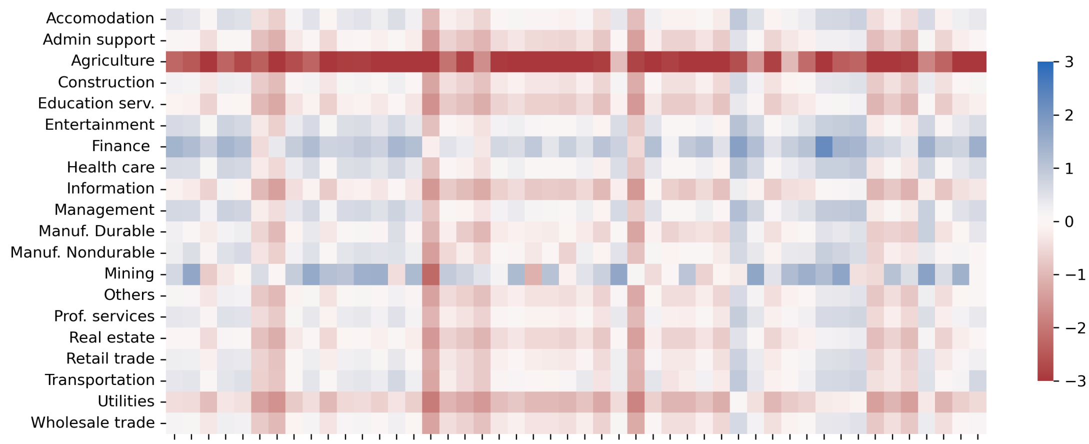
The results from both panels underscore the presence of heterogeneities across sectors and states, alongside the differences that emerge between small and large weather fluctuations due to the nonlinear dynamics embodied in the regression. Mild and occasionally positive impacts characterize the effects of small shocks, while large shocks mainly yield larger and negative outcomes. This is particularly seen in states like Arizona, Alabama, New Mexico, and Virginia. In those states, a small weather shock induces a rise in the economic activity of some sectors, such as manufacturing of durable and nondurable goods, entertainment, finance, and health care. Conversely, large weather

[7]with a variance: $\sigma^2_{\hat{\theta}_{n,1}} + \sigma^2_{\hat{\theta}_{j,1}} + (\tilde{\tau}^o)^2\left(\sigma^2_{\hat{\theta}_{n,2}} + \sigma^2_{\hat{\theta}_{j,2}}\right) + 2\sigma_{\hat{\theta}_{n,1},\hat{\theta}_{j,1}} + 2\tilde{\tau}^o\left[\sigma_{\hat{\theta}_{n,1},\hat{\theta}_{n2}} + \sigma_{\hat{\theta}_{n,1},\hat{\theta}_{j,2}} + \sigma_{\hat{\theta}_{j,1},\hat{\theta}_{n,2}} + \sigma_{\hat{\theta}_{j,1},\hat{\theta}_{j,2}}\right] + 2(\tilde{\tau}^o)^2\sigma_{\hat{\theta}_{n,2},\hat{\theta}_{j,2}}$

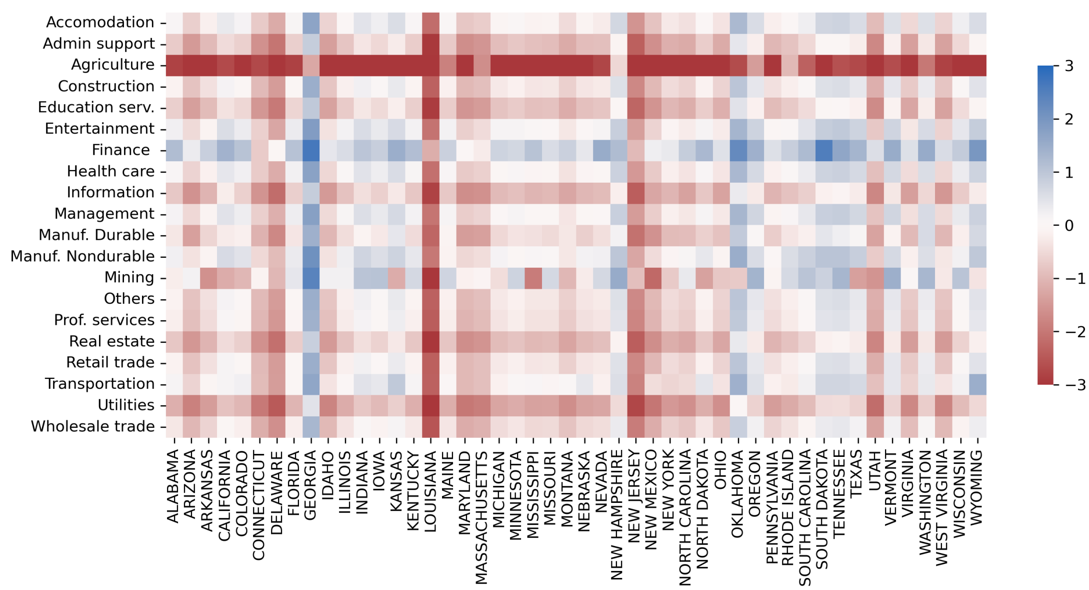
[8]As reported by the NOAA, the average increase in temperature per decade was around 0.27 Celsius degree since 1980.

Figure 2. Contemporaneous impact of weather fluctuations on growth rate by sector-state

(a) Small shock: $\tilde{\tau}^o = 0.5\sigma_{\tilde{\tau}}$



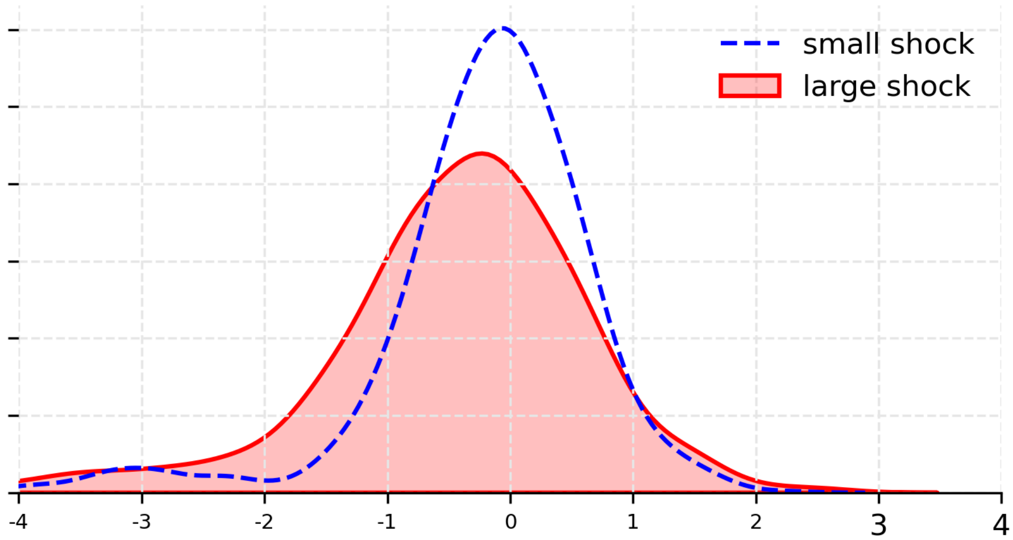
(b) Large shock: $\tilde{\tau}^o = 1.5\sigma_{\tilde{\tau}}$



Note: Panels (a) and (b) showed the difference in the growth rate with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. A small shock equals 0.5 standard deviations of $\tilde{\tau}$ being approximately 0.3 Celsius degree, while a large shock is defined as 1.5 standard deviations (close to one Celsius degree). Reductions in the growth rate are shaded in red, while increments are in blue.

shocks contract the performance of almost every sector. As expected, agriculture is the sector more negatively impacted by weather fluctuations. This impact seems to be evenly distributed across states when contrasted with other sectors. At a geographical level, Connecticut, Delaware, Louisiana, New Jersey, and New Mexico appear as the states most negatively affected by a large temperature rise. Interestingly, temperature increments look

Figure 3. Distribution of $\mathcal{G}_{ln}(\tilde{\tau}^o)$



Note: Figure plots a comparison between the distributions of $\mathcal{G}_{ln}$ under both sizes of shocks.

to be beneficial for Georgia. This could be related to migration patterns and housing conditions, which attract people from close but more expensive states like Florida. However, a more rigorous analysis is required to verify the validity of the results for those states.

To conclude with this part, in Figure 3, I compare the distribution of $\mathcal{G}_{lg}$ under both types of shocks. The dashed blue line denotes the histogram of $\mathcal{G}_{lg}$ induced by a small $\tilde{\tau}$, whereas the shade red histogram is related to large fluctuations. This contrast reveals a discernible shift towards the left under the influence of a large weather shock, where the simple average impact per unit Celsius passes from -0.19% to -0.45%. This is accompanied by a spreader distribution; the variance increases from 0.74 to 1.17, leading to the emergence of a "fat left tail". These changes support the relevance of the nonlinear effects, highlighting the more pronounced negative effects on economic growth rates due to larger weather shocks.

- Impact of weather shocks at the state and sectoral level

A second outcome derived from regression 10 encompasses the aggregate effects across multiple dimensions. Those include the impact at the state level denoted by $\mathcal{G}_n(\tilde{\tau}^o_{n,t})$, at the industry level represented as $\mathcal{G}_j(\tilde{\tau}^o_{n,t})$. As shown by equation 8, I can compute each of these objects using the following relations:

$$\mathcal{G}_n(\tilde{\tau}^o_{n,t}) = \sum_j w^a_{jn}\mathcal{G}_{jn}(\tilde{\tau}^o_{n,t}), \qquad w^a_{jn} = \frac{1}{T}\sum_t \left(\frac{nominal\,GSP_{jn}}{\sum_j nominal\,GSP_{jn}}\right)_t \tag{12}$$

$$\mathcal{G}_l(\tilde{\tau}^o_{n,t}) = \sum_g w^b_{ln}\mathcal{G}_{ln}(\tilde{\tau}^o_{n,t}), \qquad w^b_{ln} = \frac{1}{T}\sum_t \left(\frac{nominal, GSP_{ln}}{\sum_g nominal\,GSP_{ln}}\right)_t \tag{13}$$

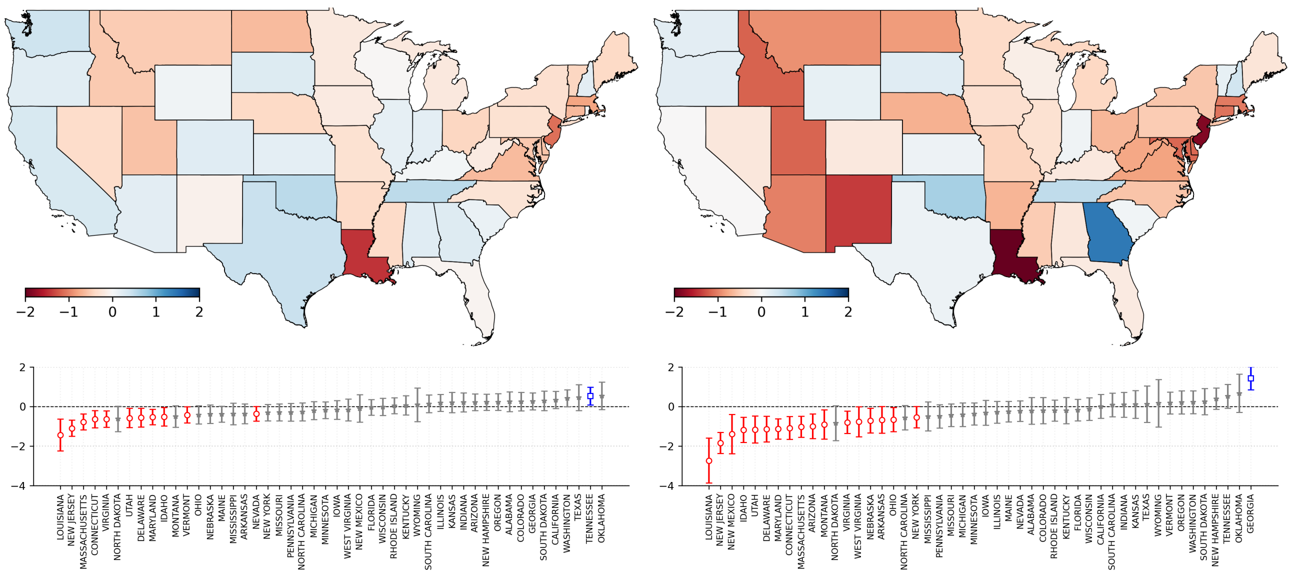
where w^a_{jn} denotes the average share of the nominal GSP the sector s on the total nominal GSP of the state n, w^b_{ln} represents the average share of the nominal GSP of the industry l situated in state n on the total GDP of the industry l.

The effect of the nonlinearities is still evident at the state level, as highlighted by panels 4a and 4b in Figure 4. These panels provide a visual representation of the spatial distribution of $\mathcal{G}_n$, accompanied by their respective 90-percent confidence intervals. To ease interpretation, blue shades correspond to positive effects on real production, while red hues denote negative effects. The results reveal that the impact of a small weather shock, when aggregated at the state level, oscillates within the range from -1.45 percent to 0.53 percent. In this regard, almost one-quarter of the states exhibit statistically negative effects. In contrast, when states face large temperature anomalies, their responses per unit Celsius span a broader interval of [-2.7%: 1.42%], with 17 out of 48 states presenting statistically significant reductions in their economic activity. Particularly, states in the Southwest, Louisiana (-2.7%), and New Mexico (-1.8%) appear to be more vulnerable to large weather anomalies.

In comparison, aggregating the impact $\mathcal{G}_{jn}$ to the industry level ($\mathcal{G}_l$) shows which sectors are, on average, more sensitive to short-run variations in temperature. Figure 5 presents the distribution of G_l under the small and the large weather anomalies. In line with the literature, agriculture production looks to be the most affected under both scenarios, with approximately a decrease of 3 percent per unit Celsius. In the case of a small shock, close to 11 out of 20 sectors exhibit no significant responses, while five sectors show negative statistically significant responses. Surprisingly, three sectors report increments in their economic activity: healthcare (0.27%), management (0.36%), and finance (0.68%). The results for the management and finance sector could be related to a higher investment appetite during "good" weather days, as shown by Dushnitsky and Sarkar (2022). These effects disappear when the economy faces a large shock. In contrast, negative responses are more accentuated under large weather fluctuations, reflecting the

Figure 4. Impact of weather fluctuations on economic activity at state level $\mathcal{G}_n$, per unit Celsius

(a) Small weather shock $\tilde{\tau}^0 = 0.5\sigma_{\tilde{\tau}}$ **(b)** Large weather shock $\tilde{\tau}^0 = 1.5\sigma_{\tilde{\tau}}$



Note: Panels (a) and (b) showed the difference in the average growth rate per state with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the sector responses using the share in nominal state GDP as weight. Contractions in the growth rate are shaded in red, while increments are in blue. The figures at the bottom show the confidence intervals for 90 percent confidence. Lines in blue with a square marker report statistically positive effects, lines in gray with a shaded triangle marker are related to a no-significant response, and lines in red with a circle marker suggest a significant negative impact.

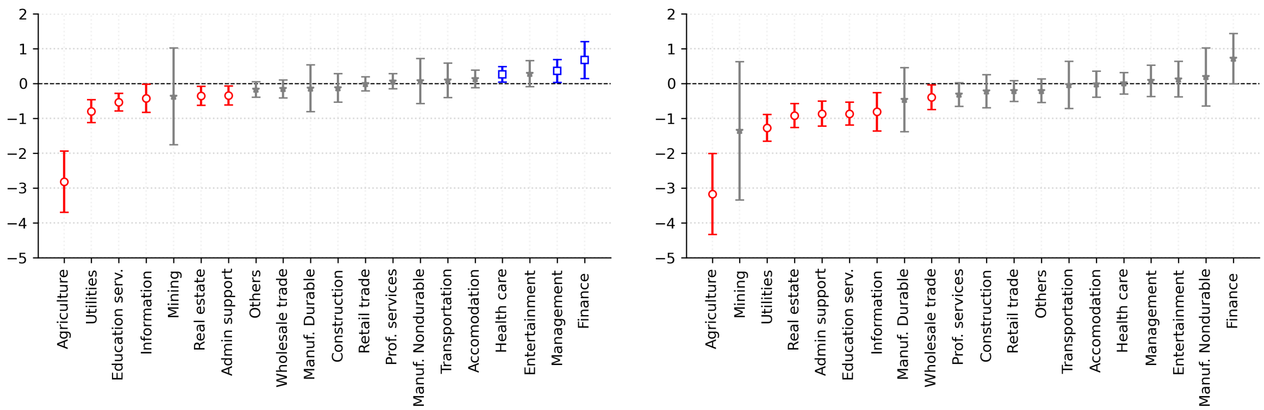
effect of the nonlinearities. For example, the contraction in utilities passes from -0.8 to -1.2, while the response of education services changes from -0.5% to -0.8%. Although, in most cases, a larger shock causes a more negative impact on the mean, the high variability across regions worsens the identification of the aggregate effect, leading to large confidence intervals and statistically no-significant responses.

- Regional contribution to $\mathcal{G}_n$

Economic activities across geographies exhibit a remarkable degree of diversity due to the confluence of infrastructure, geography, resources, and historical influence. For example, geographies with abundant natural resources will have an economy more oriented toward extractive industries. Conversely, states with large urban centers tend to emphasize service sectors. Figure 6 illustrates the sectoral composition of the 48 considered states, revealing the diversity in economic structures. Given these disparities, a natural question arises: To what degree are the differences in sectoral composition among states explaining the observed heterogeneity in the response to weather anomalies? The

Figure 5. Impact of weather fluctuations economic activity at industry level $\mathcal{G}_l$, per unit Celsius

(a) Small weather shock $\tilde{\tau}^0 = 0.5\sigma_{\tilde{\tau}}$ **(b)** Large weather shock $\tilde{\tau}^0 = 1.5\sigma_{\tilde{\tau}}$



Note: Panels (a) and (b) showed the difference in the average growth rate per industry with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the state's responses within the same industry using the state's share in nominal GDP of the specific as weigh. Lines in blue with a square marker report statistically positive effects, lines in gray with a shaded triangle marker are related to a no-significant response, and lines in red with a circle marker suggest a significant negative impact. Confidence intervals cover a probability of 90 percent.

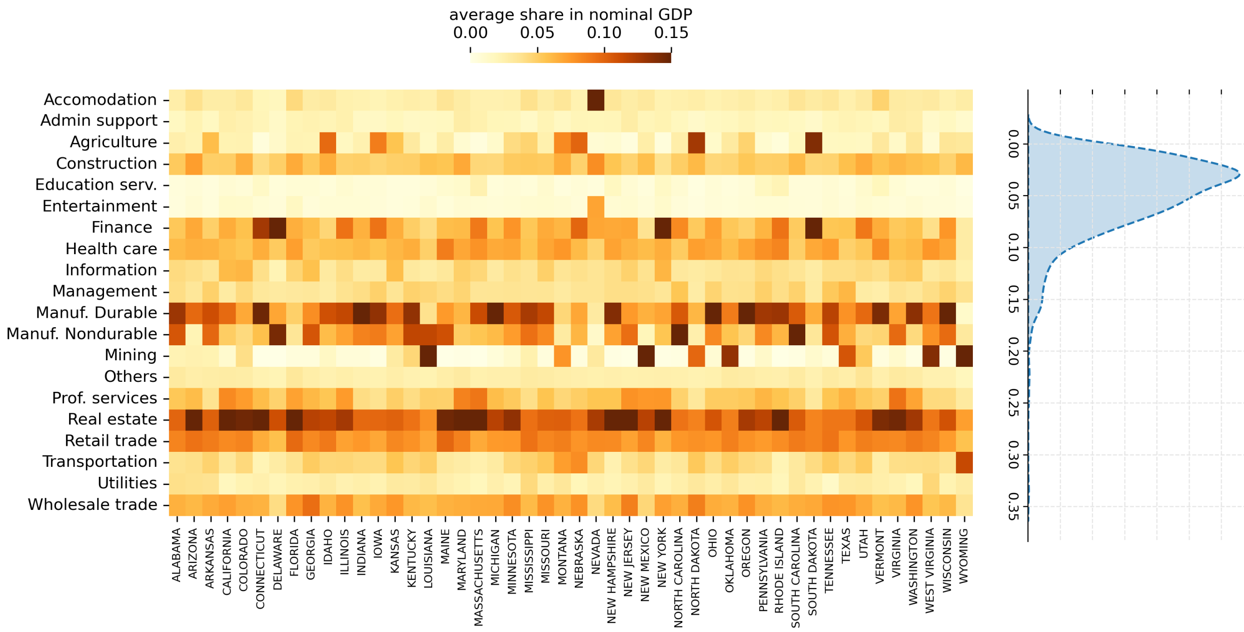
answer to this question holds relevance for two main reasons. First, isolating the role of economic structures and geographical particularities in the reported results helps policymakers decide the more efficient set of instruments to be used in a world with limited implementability. Second, recognizing the relevance of regional factors may require state authorities to build different approaches to assess the risk involved.

Let $\bar{w}^a_j = \frac{1}{T}\sum_t \left(\frac{nGDP_{jt}}{nGDP_t}\right)_t$ denote the share of the sector j in the aggregate economy and $\mathcal{G}_j$ represent the average impact of weather fluctuations on the sector j. Then, by exploiting the linearity of the aggregation $\mathcal{G}_n$, I can propose the following decomposition:

$$\mathcal{G}_n = \underbrace{\sum_j \bar{w}^a_j \mathcal{G}_j}_{\substack{\text{economy-wide}\\ \text{effect}}} + \overbrace{\sum_j \tilde{w}^a_{jn} \mathcal{G}_j}^{\substack{\text{dev. due to}\\ \text{economic struct.}}} + \underbrace{\sum_j w^a_{jn} \tilde{\mathcal{G}}_{jn}}_{\substack{\Delta \text{ due to}\\ \text{region-specific}\\ \text{conditions}}}, \qquad \bar{w}^a_j = \frac{1}{T}\sum_t \left(\frac{nominal\ GDP_{jt}}{nominal\ GDP_t}\right)_t \tag{14}$$

where variables with tilde $\tilde{w}^a_j = w^a_{jn} - \bar{w}^a_j$ and $\tilde{\mathcal{G}}_{jn} = \mathcal{G}_{jn} - \mathcal{G}_j$ are defined as the differences of the state-specific value of the variable with respect to its average. The first component of equation 14 represents the economy-wide effect, which I assume is unrelated to specific

Figure 6. Economic structure by state



Note: Figure in the left shows a heatmap of the economic structure by state. In this paper, I understand economic structure as how the total economic activity of a state is distributed among sectors. In simple terms, the set of share of the nominal GDP of a sector j on the total nominal GDP of the state n. The figure on the right displays the histogram of these shares.

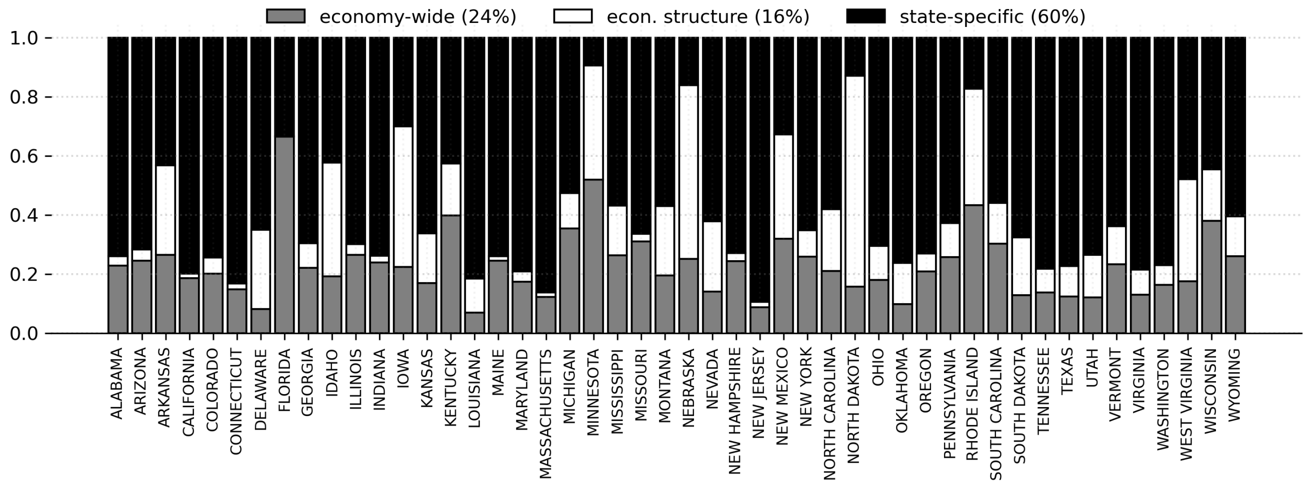
geographical factors. The second component, $\sum_j \tilde{w}^a_{jn} \mathcal{G}_j$, shows the fraction driven solely by differences in sectoral composition, which I will use as a proxy of the relevance of the economic structure. Finally, the last component $\sum_j w^a_{jn} \tilde{\mathcal{G}}_{jn}$ captures the effect of geographically-specific conditions.

Figure 7 plots the contribution of each of these components under the small (panel 7a) and the large weather anomaly (panel 7b). To prevent the cancellation of positive and negative values, the three components were expressed in absolute terms. Then, the plot is designed to sum up 100 percent, representing each component's relative importance. The economy-wide component is depicted in gray shading, the component associated with the differences driven by economic structure is plotted in white, and the fraction explained by region-specific conditions is displayed in black.

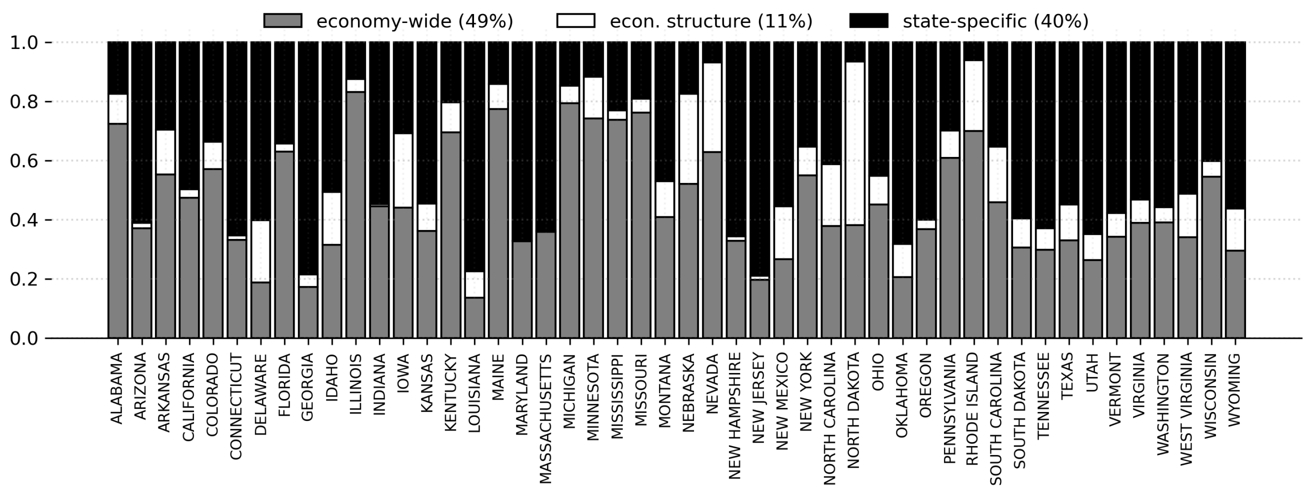
Results show that the deviations with respect to the economy-wide component are mostly explained by regional-specific conditions reflecting the importance of the geographical dimension and how economic activity is shaped by the environment. In the case of a small weather shock, the differences in economic structure are responsible for around 16 percent of the heterogeneity, while the regional-specific conditions account for nearly 60 percent. When regions face a large weather anomaly, the contribution of these

Figure 7. Decomposition of $\mathcal{G}_n$

(a) Small weather shock



(b) Large weather shock



Note: Panel (a) and (b) show the relative importance of the economic structure, state-specific conditions, and an economy-wide component to explain the average response of each state.

components reduces to 11 percent and 42 percent, respectively. The lower explanation power of both components is not surprising since larger temperature anomalies drive large reductions in most states, increasing the economy-wide component.

- Contribution of weather variability to economic performance

This article proposes a nonlinear model to study the short-run implications of weather fluctuations on growth rates. However, a particularity of the proposed model is that even if the average of the temperature anomalies is equal to 0, long-run effects are still possible due to the nonlinear nature of 10. In fact, the expected impact of weather variability on economic growth rates, which I denote as $\mathcal{H}_{jn}$, is different from zero and depends on the variance of the weather anomalies ($\sigma^2_{\tilde{\tau}_n}$). I construct $\mathcal{H}_{jn}$ as the difference between a counterfactual scenario characterized by temperature values that do not deviate from their short-run trend[9] and the observed growth rates. Mathematically, $\mathcal{H}_{jn}$ and their aggregate at the state level ($\mathcal{H}_n$) and at the industry level ($\mathcal{H}_n$) can be calculated with the formulas:[10]

$$\mathcal{H}_{jn} = \mathbb{E}[\Delta y_{jnt}] - \mathbb{E}[\Delta y_{jnt} | \{\tilde{\tau}_{nt} = 0\}_{-\infty}^{\infty}] = \frac{\hat{\theta}_{n,2} + \hat{\theta}_{j,2}}{1 - \hat{\rho}_j} \sigma^2_{\tilde{\tau}_n} \tag{15}$$

$$\mathcal{H}_n(\sigma^2_{\tilde{\tau}}) = \sum_s w^a_{jn} \mathcal{H}_{jn}(\sigma^2_{\tilde{\tau}}) \tag{16}$$

$$\mathcal{H}_l(\sigma^2_{\tilde{\tau}}) = \sum_g w^b_{ln} \mathcal{H}_{ln}(\sigma^2_{\tilde{\tau}}) \tag{17}$$

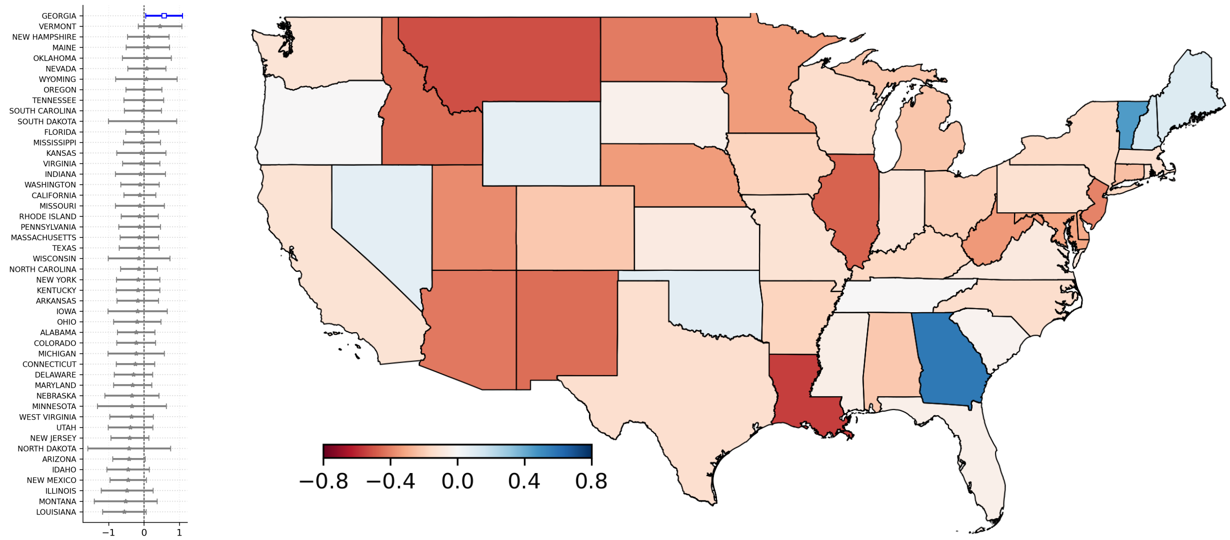
The distribution of $\mathcal{H}_n$ and its confidence interval for a probability range of 90 percent plotted in figure 8 support the short-run nature of my exercise. In average terms, we can see that most states would benefit from a scenario without short-run deviations in temperature. In particular, the states of Louisiana (-0.55%), Montana (-0.52%), Illinois (-0.47%), and New Mexico (-0.45%) would be the more benefited under the counterfactual scenario. However, in 47 cases, the confidence interval shows that this expected effect is not statistically significant, suggesting that my approach successfully isolates only fluctuations in the short run.

[9] In simple terms, this counterfactual scenario assumes that $\tilde{\tau}_{nt}$ remains constant at 0 for the whole sample

[10] Using a Taylor approximation, we have that $VAR\left(\frac{X}{Y}\right) = \frac{1}{(\bar{Y})^2} var(X) + \frac{(\bar{X})^2}{(\bar{Y})^4} var(Y) + \frac{\bar{X}}{(\bar{Y})^3} cov(X,Y)$. Applying it to $\mathcal{H}_{jn}$ and assuming $\sigma^2_{\tilde{\tau}}$ being constant, I have:

$$var(\mathcal{H}_{jn}) = \sigma^2_{\tilde{\tau}} \left[\frac{1}{(1-\hat{\rho}_j)^2} \left(\sigma^2_{\hat{\theta}_{n,2}} + \sigma^2_{\hat{\theta}_{j,2}} + 2cov(\hat{\delta}_{2n}, \hat{\gamma}_{2j}) \right) + \frac{(\hat{\theta}_{n,2} + \hat{\theta}_{j,2})^2}{(1-\hat{\rho}_j)^4} \sigma^2_{\hat{\rho}_j} + 2 \frac{\hat{\theta}_{n,2} + \hat{\theta}_{j,2}}{(1-\hat{\rho}_j)^3} \left(cov(\hat{\theta}_{j,2}, \hat{\rho}_j) + cov(\hat{\theta}_{j,2}, \hat{\rho}_j) \right) \right]$$

Figure 8. Contribution of weather variability to growth rates at state level $\mathcal{H}_n$



Note: Expected contribution of weather variability to economic growth by state. The map on the right shows the spatial distribution of the expected values. Negative contributions are shaded in red, while positive contributions are in blue. Confidence intervals are shown on the left and cover a probability of 90 percent.

4 The model with production networks

In this section, I show how accounting for the interconnectivity of economic activities across the different states changes the estimated impacts of weather anomalies on growth rates across regions and sectors of the economy. An easy way to introduce such linkages in the previous model is by allowing intermediate good producers to use regional-specific final goods as intermediate inputs or materials in their production process while maintaining everything else equal. As before, I denote a particular geography and its final good by $n \in \{1, \ldots, N\}$ or m and a particular intermediate sector as $j \in \{1, \ldots, J\}$ or i. I use sector (j, n) or sector (i, m) to denote a specific combination of sector and region. The new production function for intermediate goods is:

$$q_n^j = z_n^j(\tilde{\tau}_n) \left(l_n^j\right)^{\tilde{\alpha}_n^j} \prod_m \left(x_{nm}^j\right)^{a_{nm}^j} \qquad \text{with} \sum_m a_{nm}^j + \tilde{\alpha}_n^j = 1 \quad \forall\, n \tag{18}$$

Here, q_n^j represents the production of sector j at state n, l_n^j is labor, where $x_{n,m}^j$ denotes the final goods m that sector (j, n) buys to use them as intermediate goods, and $\{a_{nm}^j\}$ are the output elasticities of these intermediate goods. In a similar fashion, the production function of State n is now:

$$Q_n = \prod_j \left(q_n^j\right)^{b_n^j} \tag{19}$$

In contrast with the previous section where y_n^j and Y_n represent value-added production functions, in both cases here, q_n^j and Q_n refer to gross output. Then, I need to add the following market-clearing conditions:

$$Q_n = c_n + \sum_m \sum_j x_{mn}^j \qquad \forall\, n \tag{20}$$

The optimality conditions for the intermediate goods and final firms are:

$$a_{nm}^j = \frac{p_m x_{nm}^j}{p_n^j q_n^j} \tag{21}$$

$$\tilde{\alpha}_n^j = \frac{w l_n^j}{p_n^j q_n^j} \tag{22}$$

$$b_n^j = \frac{p_n^j q_n^j}{p_n Q_n} \tag{23}$$

At equilibrium, the ratio of expenditures on inputs x_{nm}^j to total sales of the sector (j, n) is fixed and can be used to infer the elasticities a_{nm}^j. Similarly, the ratio of expenditure on intermediate goods (j,n) to total sales of the region n is constant and is determined by the parameter b_n^j. Defining the real value added of the sector (j,n) as the total payroll in real terms $y_n^j = \frac{w l_n^j}{p_n^j}$, we can see from Equation 22 that the ratio y_n^j to q_n^j is constant and determined by the labor elasticity $\tilde{\alpha}_n^j$. Therefore, we can express fluctuations in the real value-added by sector-state as:

$$d \ln y_n^j = d \ln q_n^j \tag{24}$$

Combining the optimality condition of the household $\frac{p_n}{p_m} = \frac{\beta_n}{\beta_m}\frac{c_m}{c_n}$, the first order condition of final-good producers and equation 21, we obtain the relation

$$x_{nm}^j = a_{nm}^j b_n^j \frac{\beta_n}{\beta_m}\frac{c_m}{c_n} q_n$$

that can be introduced in the market clearing condition to reach the following result:

$$\frac{q_n}{c_n} = 1 + \sum_m \left(\frac{\beta_m}{\beta_n} \sum_j a_{mn}^j b_m^j\right) \frac{q_m}{c_m} \tag{25}$$

Equation 25 shows that, in the equilibrium, the share of the production of the final good

n that is directly consumed by the household is constant and independent of productivity shocks. It implies that at the state level, fluctuations in final consumption are equal to fluctuations in gross output.

$$d \ln Q_n = d \ln c_n \tag{26}$$

Taking logs and differentiating both sides of the production function of intermediate sectors and realizing that at equilibrium l_i is constant leads to:

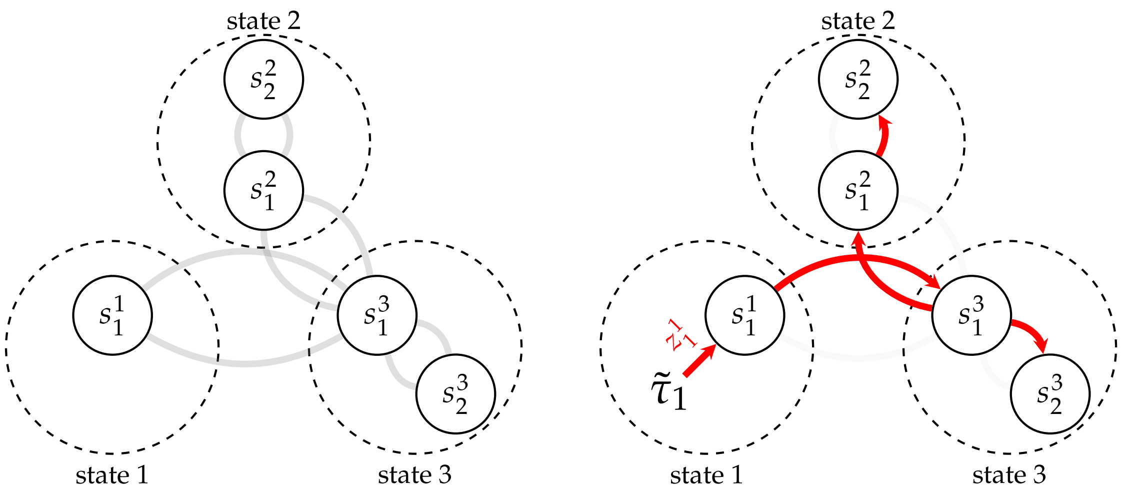
$$d \ln y_n^j = d \ln z_n^j(\tilde{\tau}_n) + \sum_{m,i} a_{nm}^j b_m^i d \ln y_m^i$$
$$\ln \boldsymbol{y} = (I - A)^{-1} d \ln \boldsymbol{z} = \Psi d \ln \boldsymbol{z} \tag{27}$$

where $\ln \boldsymbol{y} = \left[d \ln y_1^1, d \ln y_1^2, ...\right]^T$ is a column vector composed of the sector-state real value added growth rates. The matrix A collects all the coefficient $b_m^i a_{nm}^j$ associated with the input-output matrix of the economy. The matrix Ψ is called the Leontief-inverse matrix. Particularly, since we can decompose Ψ as an infinite sum of the power of the input-output matrix $\Psi = \sum_{s=0}^{\infty} A^s$, each element of Ψ gives us an idea of the total impact of a particular fluctuation z_m^i has in all the other sectors y_n^j of the economy. Finally, this expression can be written as:

$$\mathrm{d} \ln y_n^j = \underbrace{\mathrm{d} \ln z_n^j(\tilde{\tau}_n)}_{\text{own effect}} + \overbrace{\sum_{i,m} (\psi_{nm}^{ji} - \mathbf{1}_{n=m}^{j=i}) \mathrm{d} \ln z_m^i(\tilde{\tau}_m)}^{\text{network effect}} \tag{28}$$

The propagation of a weather shock through the economy can be understood using a simple example. Suppose an economy comprises three states and two sectors, one producing a nontradable good s_2. Moreover, suppose that State 1 produces only the good s_1 and trades it only with State 3. This setup is depicted in the left panel of Figure 9. To ease the explanation, let s_j^n denote the production of the good j in the state n. As shown by the panel (b) of the same figure, if State 1 faces a weather shock $\tilde{\tau}_1$, this shock initially reduces the productivity of the firms in State 1 and contracts the production of s_1^1. Since State 3 buys s_1 from State 1 as intermediate input to produce good 1, its production is directly affected in the first round. Given that s_1^3 is used as an intermediate input for s_1^2 and the nontradable good s_2^3, the production of both reduces in a second round. This pattern continues, creating a cascade of negative shocks. This simple example allows us to visualize the importance of accounting for these network effects to capture the actual impact of weather shocks on the whole economy.

Figure 9. Transmission of a state-specific weather shock



(a) Trading connections in the economy **(b)** Propagation of a weather shock in State 1

As in the previous section, the optimality conditions imply the following aggregation rule:

$$d \ln c_n = \sum_j b_n^j d \ln y_n^j \tag{29}$$

$$d \ln C = \sum_{n,j} \beta_n b_n^j d \ln y_n^j \tag{30}$$

Therefore, I can use b_n^j as an aggregator at the state level and β_n as an aggregator from state to aggregate.

4.1 Empirical implementation

Equation 28 reveals the relevance of the Leontief-inverse matrix Ψ derived from an Input-Output (A) table constructed at a sector-state level to test whether interregional linkages contribute significantly to the propagation of weather fluctuations into the economy. Unfortunately, available data is not sufficient to compute this Leontief-inverse directly; consequently, an approximation is required. I denote this empirical approximation of A as $\mathcal{A}$. To construct $\mathcal{A}$, I rely on data from the USE table and the Commodity Flow Survey

(CFS) and employ some critical assumptions. In the following paragraphs, I describe each source of information and my approximation strategy.

The "USE table" is a component of the input-output accounts provided by the Bureau of Economic Analysis (BEA) on a five-year basis. This table reports the aggregate transactions between the different sectors of the economy. Specifically, each entry (i, j) in the USE table shows the total spending of sector s_j on goods produced by sector s_i. Additionally, the USE table included information about the Gross Output of each sector. Therefore, the USE table provides detailed information about the intermediate inputs used and the Value Added (VA) generated by each sector. Leveraging these details, I can construct the Input-Output (IO) matrix at the sector level for the whole economy where each element $IO_{ij} = \frac{\text{USE}_{ji}}{\sum_{l \in S} \text{USE}_{lj} + VA_j}$ represents the average requirement that a typical firm in the sector s_i has for intermediate inputs produced by sector s_j measured as a ratio to its total sales.

I "regionalize" the parameters $\{a_{ij}\}$ using information from the Commodity Flow Survey. The CFS is a survey conducted every five years by the U.S. Census Bureau in collaboration with the Department of Transportation Bureau of Transportation Statistics[11]. It gathers comprehensive data on shipments within the states of the United States. The collected data includes details such as the state of origin and destination, the NAIC classification of the product being shipped, the value of the shipment, and the export status. After subtracting shipments that would be exported, I obtained 24 matrices $B(j)$ with the information on interregional trade for 24 tradable sectors. Each entry (i, j) of $B(j)$ represents the total value of the j-goods shipped from state j to state i. I classified the remaining 35 sectors as not tradable (see the appendix).

It is important to note that CFS does not specify the final user of these shipments, preventing distinguishing whether these shipments are used as intermediate inputs or for final consumption. Moreover, within the fraction of the shipments that are being used as an intermediate input, it is impossible to identify the specific proportions that each sector is purchasing. To handle these challenges, I assume that for a given good j, the sector sales structure s_j is homogeneous across the geographies, and they follow what the IO reports. This assumption has two main implications. Firstly, since the fraction of total sales that are sold towards final consumption is the same across states, it is not required to discount sales to final consumers from matrices B if they are expressed as shares rather than in dollar value. Let $\tilde{B}(j)$ denote a transformation of $B(j)$ such that each (l, m)-element

[11]The most recent available CFS data was released in 2021, containing data from 2017

$\tilde{b}^{l,m}_{,j} = \frac{b^{l,m}_{,j}}{\sum_h b^{l,h}_{,j}}$ is the fraction of the expenditures of the state l on [final or intermediate] goods j that comes from the state m. Secondly, since the distribution of sales a good j as intermediate inputs is independent of the geography, the ratios $\tilde{b}^{l,m}_{,j}$ are fixed across the sectors within the state l for a particular intermediate input j. Nontradable goods, can be easily accommodated by noting that $\tilde{B}(j)_{j\in \text{nontradable}}$ is an identity matrix, implying that $\tilde{b}^{l,m}_{,j\in \text{nontradable}} = 1_{l=m}$ and zero otherwise. This implicitly assumes that nontradable sectors buy exclusively from sectors within the same state, reducing the exposure of such sectors to weather shocks from another region. Then, I can approximate the requirement of the pair sector-state (i,l) for intermediate goods from the pair (j,m) as: $\mathcal{A}^{l,m}_{i,j} = \tilde{b}^{l,m}_{,j} a_{i,j}$

Let $\tilde{\tau}^{network}_{jnt}$ denote the weather shock faced by a sector j located within the state n at time t, which arises solely due to network-related connection computed as the average of other regional weather anomalies $\tilde{\tau}_n$ weighted by the components of the previously calibrated Leontief-inverse. Then, the empirical counterpart of equation 28 to be estimated is:

$$\begin{aligned}\Delta\tilde{y}_{j,n,t} = \alpha + \rho_j \Delta\tilde{y}_{j,n,t-1} + \left(\theta_{n,1} + \theta_{j,1}\right)\tilde{\tau}_{n,t} + \left(\theta_{n,2} + \theta_{j,2}\right)\tilde{\tau}^2_{n,t} + \\ \zeta_{1n}\tilde{\tau}^{network}_{jnt} + \zeta_{2n}\left(\tilde{\tau}^{network}_{jnt}\right)^2 + \gamma_j + \gamma_n + \gamma_t + \epsilon_{j,n,t} \qquad (31)\end{aligned}$$

Although regression 10 exploits possible heterogeneities across sectors and states, it is important to acknowledge that including additional explanatory variables introduces limitations regarding the dimensions in which heterogeneity can be explored arising from the reduction of power in the estimation due to data limitations. In that sense, I only consider potential differences in the sensitivity to $\tilde{\tau}^{network}_{jnt}$ across geographies. Two reasons support this decision. First, as inferred from the outcomes of the preceding regression, the regional differences in the impact of weather fluctuations are mostly explained by geographical conditions rather than sectoral composition, implying that not including this dimension would result in larger biases in the analysis. The second reason is technical. Allowing heterogeneity across sectors reduces the estimation precision due to the additional 22 coefficients that must be estimated and the set of variances and covariances that characterize their distribution.

- Contemporaneous impact of weather fluctuations on economic activity

Similar to regression 10, we can calculate the total effect of a specific weather shock $\tilde{\tau}^0$ state-by-state. However, including networks adds complexity to constructing a counterfactual scenario. For example, in the model where only heterogeneity was considered, the results at the state level are valid whether each state faces the weather shocks simultaneously or at different times. In contrast, in an economy with network linkages, weather shocks propagate internally among sectors within the same state and externally across states. These propagation patterns imply that state-level results depend on the set of simultaneous shocks that the whole economy faces. To maintain coherence with the spirit of the counterfactual scenario posted in the previous sections and to avoid aggregation problems, I simulated a scenario where the temperature in all states increases simultaneously by the same amount $\tilde{\tau}^o$ which I call a generalized weather shock scenario. Under this scenario, the total effect per unit Celsius is

$$\mathcal{G}_{jn}^{network}(\tilde{\tau}^o) = \underbrace{(\hat{\theta}_{n,1} + \hat{\theta}_{j,1}) + (\hat{\theta}_{n,2} + \hat{\theta}_{j,2})\tilde{\tau}^o}_{\text{direct effect/exposure}} + \overbrace{\hat{\zeta}_{1n}\ell_{jn} + \hat{\zeta}_{2n}\ell_{jn}^2\tilde{\tau}^o}^{\text{network effect/exposure}} \qquad \ell_{jn} = \sum_{i,m}\left(\psi_{jn,im} - \mathbf{1}_{jn=im}\right) \tag{32}$$

This model uses the ratio of gross output as weight (Equation 29) to aggregate from sector-state to state level. Unfortunately, there is no data on gross output at the neither sector-state nor the state level. Then, I assume that the weights previously used, which are based on nominal GDP, are good proxies. Therefore, all the aggregations from $\mathcal{G}_{ln}$ were based on the same aggregators as in the first model.

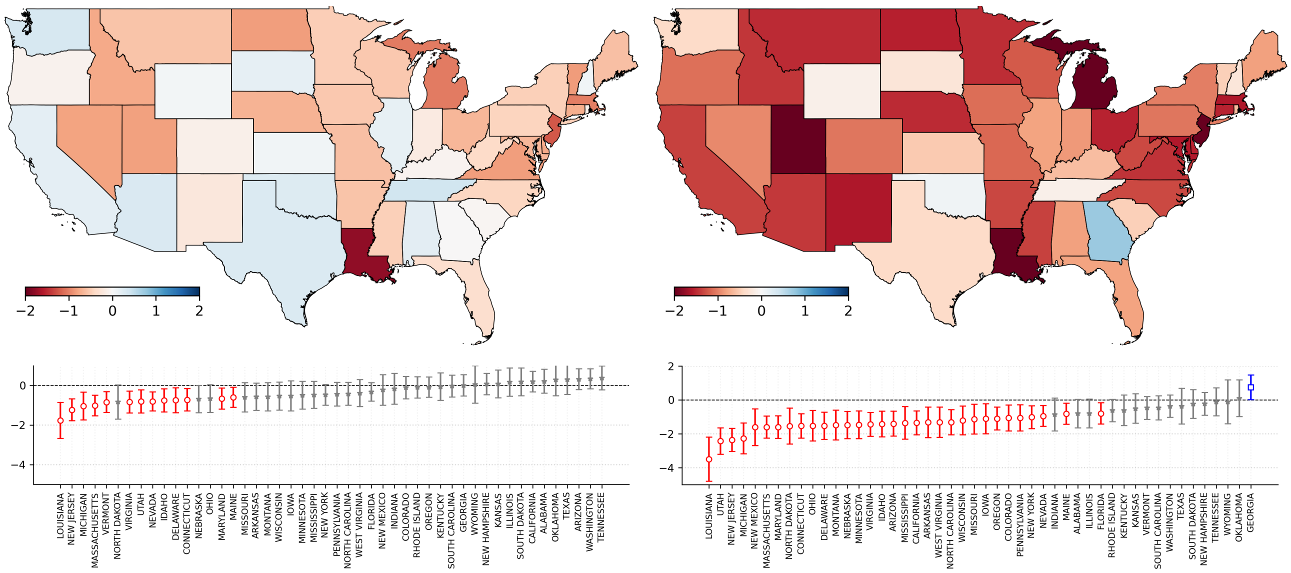
At a geographical level[12], a large weather shock causes a statistically significant reduction in real output in most states consistent with the role of the amplifier of the network. These results are plotted in Figure 10, which presents the effect -per unit Celsius- of small and large weather fluctuations on economic activity at the state level. Similarly to the model with only heterogeneity, small weather fluctuations cause significant negative impacts only in one-quarter of the states (panel 10a). In contrast, large shocks cause statistically significant reductions in the real production of 32 states, which is almost double the number of states affected negatively when only heterogeneities are accounted for. The transmission of negative effects through network linkages looks particularly

[12]The results can be aggregated using the same weights as in the previous section.

strong for the states in the West and Middle-West regions of the United States, such as California, Oregon, and Michigan.

Figure 10. Impact of weather fluctuations at state level $\mathcal{G}_n$, per unit Celsius

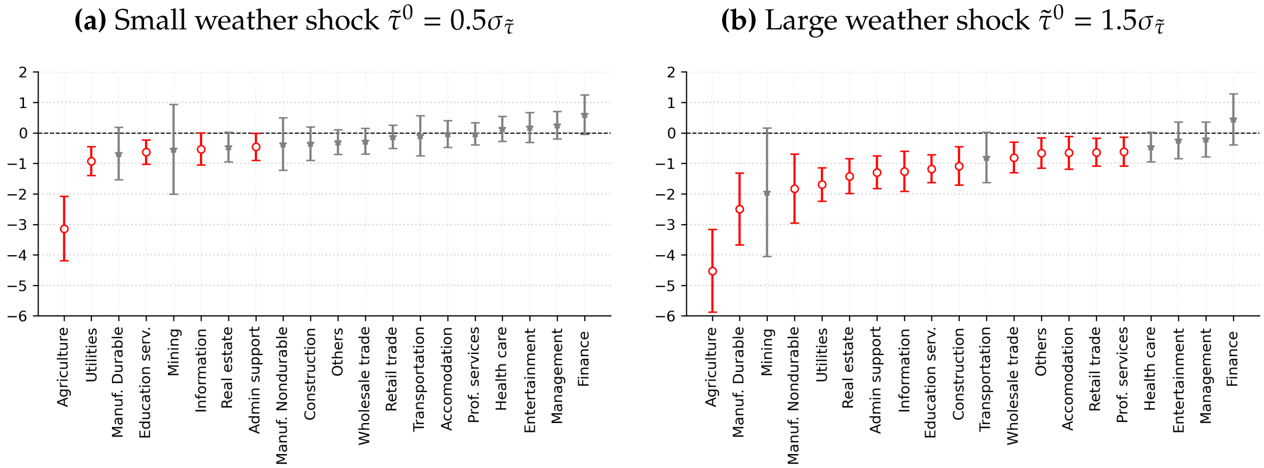
(a) Small weather shock $\tilde{\tau}^0 = 0.5\sigma_{\tilde{\tau}}$ **(b)** Large weather shock $\tilde{\tau}^0 = 1.5\sigma_{\tilde{\tau}}$



Note: Panels (a) and (b) showed the difference in the average growth rate per state with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the sector responses using the share in nominal state GDP as weigh. Contractions in the growth rate are shaded in red, while increments are in blue. The figures at the bottom show the confidence intervals for 90 percent confidence. Lines in blue with a square marker report statistically positive effects, lines in gray with a shaded triangle marker are related to a no-significant response, and lines in red with a circle marker suggest a significant negative impact.

As depicted by Figure 11, accounting for sectoral interactions amplifies the negative effect of weather shocks on both tradable and nontradable sectors. This figure provides valuable insights. First, from panel (a), we see that the positive effect of small weather shocks on the economic activity of sectors like Finance disappears when we account for economic linkages. Second, when the economy faces a large weather shock, production reduces in 14 out of 20 sectors, as displayed by panel 11b, which almost doubles the results of the model with only heterogeneity. In particular, both types of manufacturing (durable and nondurable) report a statistically significant contraction of around -2.5 percent and -1.8 percent, respectively. Third, although the transmission mechanism relies on interregional trade flows, its effects are also visualized in non-tradable sectors. This is particularly the case for Construction and Accommodations that pass from not showing significant responses to reporting statistically significant negative responses.

Figure 11. Impact of weather fluctuations at industry level $\mathcal{G}_l$, per unit Celsius



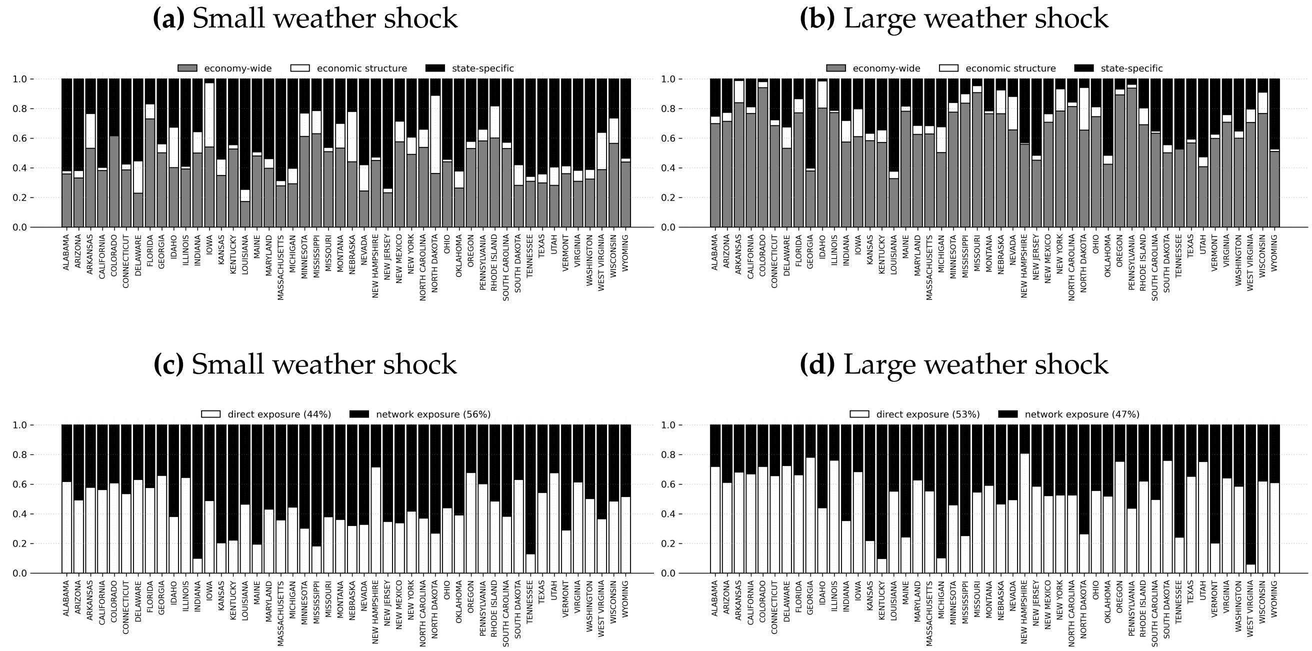
Note: Panels (a) and (b) showed the difference in the average growth rate per industry with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the state's responses within the same industry using the state's share in nominal GDP of the specific as weigh. Lines in blue with a square marker report statistically positive effects, lines in gray with a shaded triangle marker are related to a no-significant response, and lines in red with a circle marker suggest a significant negative impact. Confidence intervals cover a probability of 90 percent.

- Decomposing the geographical differences in $\mathcal{G}_{jn}^{network}$

In a model with interregional linkages, there are two relevant dimensions in which the heterogeneity in $\mathcal{G}_{jn}^{network}$ can be decomposed. The first dimension explains the economic source of these differences by isolating the fraction of the impact explained by differences in the economic structure and the portion related to sector-state-specific conditions. I provided a way to measure both components in the previous section. The second dimension identifies the geographical sources of these differences by quantifying the extent to which $\mathcal{G}_{n}^{network}$ is driven by weather shocks within the state g itself and how much is explained by the weather conditions of other states that in equation 28, we called as direct and network effect, respectively. Both decompositions are shown in Figure 12.

Although the introduction of network linkages increases the relevance of the economy-wide component, differences in the sensitivity to weather shocks across states are mainly explained by state-specific conditions. Panels (a) and (b) of Figure 12 show the decomposition of $\mathcal{G}_n$ by economic source. On average, the portion explained by state-specific conditions, depicted as black shaded bars, explains 46 percent of the total effect when the economy is hit by a small weather shock. This value reduces to 26% in the scenario of a large weather shock. In contrast, differences in economic structure contribute to 12 and 8 percent, respectively. Notably, the economic structure component is more relevant for North Dakota, Iowa, and Nebraska, contributing more than 33 percent to the total effect under small weather shocks. Both the direct and network effects explain a good portion of the total impact of weather fluctuations on the economy, as depicted by panels (c) and (d) of Figure 12. On average, the contribution of the network effect is around 53 percent (56 % during small shocks and 47% during large shocks).

Figure 12. Decomposition of $\mathcal{G}_n^{network}$



Note: Panel (a) and (b) show the relative importance of the economic structure, state-specific conditions, and an economy-wide component to explain the average response of each state. Panel (c) and (d) present the decomposition of $\mathcal{G}_n^{network}$ in their geographical sources: (i) direct effect: the total effect caused by temperature anomalies in their region and (ii) indirect effect: the impact of temperature anomalies from other regions

5 Macroeconomic implications of heterogeneity and network linkages

In the previous sections, I showed that there is high variability in the local impact of weather fluctuations on economic growth across sectors and states. I also show that including networks amplifies the economic contraction caused by a widespread temperature increase at the sector-state level due to the exposure to weather fluctuations from other regions. In this section, I explore the macroeconomic implications of both channels.

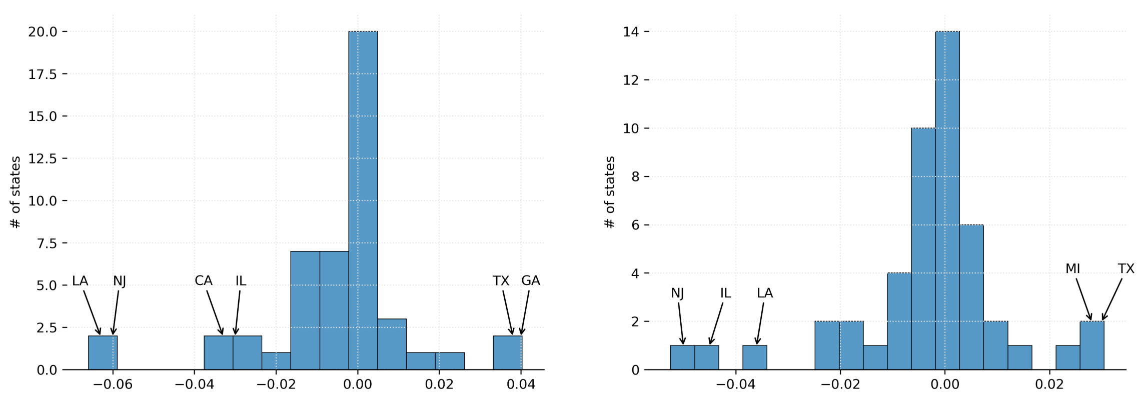
In his "granular" hypothesis, Gabaix (2011) suggests that idiosyncratic shocks to large firms have nontrivial aggregate effects in concentrated economies. In the United States, almost one-third of the economic activity is concentrated in California (13%), New York (9%), Texas (8%), and Illinois (5%). A first approximation of the macroeconomic relevance of production networks is to test whether weather fluctuations originating in the largest states generate the most significant aggregate impact. I approach it with a counterfactual analysis. In this scenario, I compute the aggregate effect of idiosyncratic weather fluctuations in a particular state. For each state n, I create a vector of pseudo-weather fluctuations t_n^{sim} in which the entry associated with the state n has a value τ_0 while the rest are set to 0. Then, I calculate a new vector of network effects $\tau_{jn}^{network}$ conditional on τ_{sim} and predict the effect on state-level real production as in the previous section. As shown by equation 30, the overall impact of weather shocks on aggregate economic activity can be computed as a weighted average of the state-level effects using the share of the nominal GDP of State n to aggregate nominal GDP as weight:

$$\mathcal{G}^{network}(\tilde{\tau}^o)\tilde{\tau}^o = \sum_n w_n^c \mathcal{G}_n^{network}(\tilde{\tau}^o)\tilde{\tau}^o, \qquad w_n^c = \frac{1}{T}\sum_t \left(\frac{nominal\ GDP_n}{nominal\ GDP}\right)_t \tag{33}$$

Based on the results of this exercise, it appears that while the largest states have some relevance, fluctuations in smaller states have a more significant impact on the overall effect of weather changes. Figure 13 provides a visual representation of this counterfactual analysis. In panel (a), each state experienced a shock of 1 degree Celsius. In panel (b), each state faced a shock equivalent to 1.5 standard deviations of their regional weather fluctuations. The results show that weather fluctuations in Louisiana, New Jersey, Georgia, and Michigan have the greatest impact on the overall GDP.

Figure 13. Aggregate impact of local weather fluctuations

(a) shock size: 1°C **(b)** shock size: $1.5\sigma_{\tilde{\tau},n}$



Note: The aggregate effects of local fluctuations were computed based on a counterfactual scenario in which weather fluctuations of a particular state received a shock while keeping constant the rest. Panel (a) shows the distribution of aggregate effects when each state faces a weather fluctuation of 1 Celsius degree. Panel (b) shows the distribution of aggregate effect when each state receives a shock equal to 1 standard deviation.

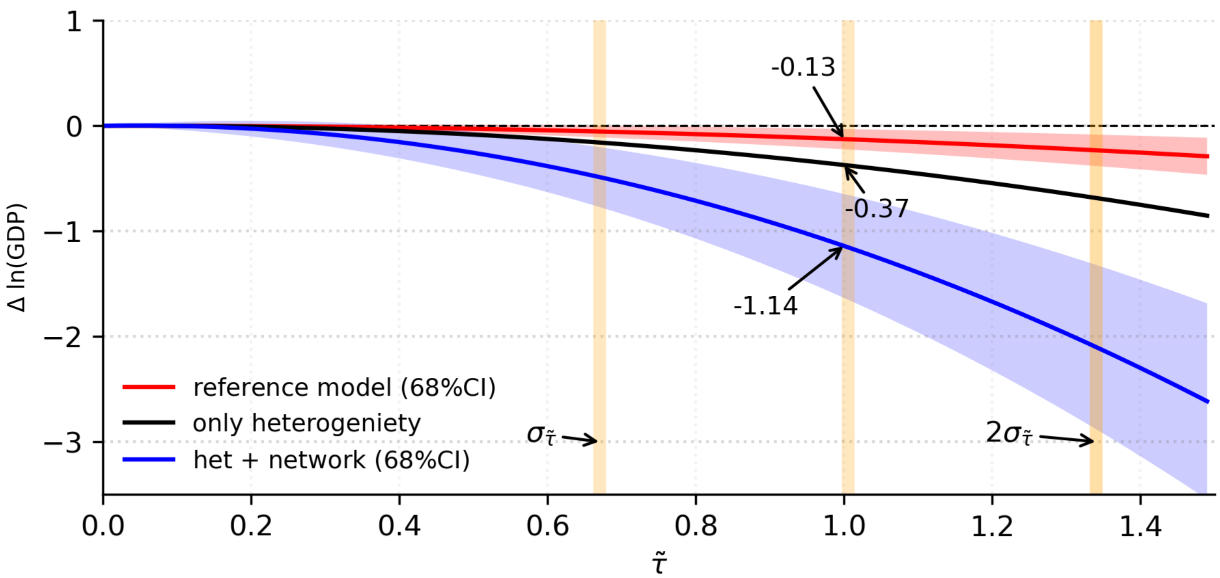
Next, I aggregate the results from the models in sections 3 and 4 as in equation 33. To provide a basis for comparison, I also include a reference point. This reference point is obtained by re-estimating specification 10, assuming constant slopes across sectors and states, thus muting the effects of heterogeneity and networks. The specific regression is:

$$\Delta\tilde{y}_{j,n,t} = \alpha + \rho\Delta\tilde{y}_{j,n,t-1} + \varphi_1\tilde{\tau}_{n,t} + \varphi_2\tilde{\tau}^2_{n,t} + \theta_j + \theta_t + \theta_n + \epsilon_{j,n,t} \tag{34}$$

from where $\mathcal{G}^{reference}(\tilde{\tau}^o) = \hat{\varphi}_1 + \hat{\varphi}_2\tilde{\tau}_{n,t}$

Figure 14 displays the estimated average impacts of weather shocks for each model at different levels of $\tilde{\tau}$ in the range from 0 to 1.5. In this figure, the red line represents the total effect on economic growth estimated by the model with no heterogeneity or networks (Equation 34). The black line refers to the model with only heterogeneity (section 3), and the blue line shows the aggregate impact of the model with networks (section 4).

Figure 14. Impact of an weather fluctuations $\tilde{\tau}$ on economic growth



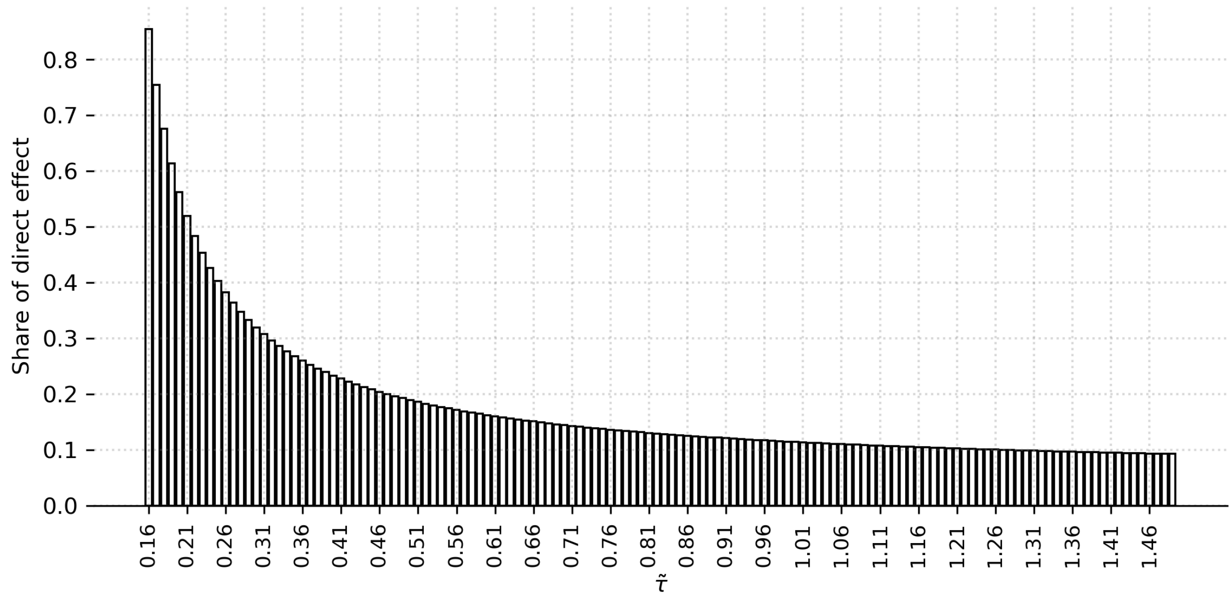
Note: Total contemporaneous impact of a generalized unanticipated shock in temperature on growth rates under different models. A generalized increase in temperature is defined as an increase in temperature in all the states simultaneously. The red line displays the impact estimated by a model without heterogeneity and networks. The black line shows the impact estimated by the model in section 3 and aggregated using share in nominal GDP as weighs. The blue line plots the aggregate impact of the model with heterogeneous response and production networks presented in section 4. the shaded areas in blue and red plot a one-standard deviation confidence interval. $\sigma_{\tilde{\tau}} \approx 0.67$ represents a standard deviation of the measure of weather fluctuations $\tilde{\tau}$

The results demonstrate that neglecting these channels underestimates the effect of widespread weather shock on economic activity. For instance, when neither heterogeneity nor networks are included, an increase in temperature of 0.3 Celsius degrees reduces the aggregate economic activity by around -0.03 percent. However, an increase in temperature of 1 Celsius degree causes a contemporaneous reduction of -0.13 percent. These impacts are higher once sector-state specific sensitivities to weather fluctuations are added. In that case, an increase in temperatures of 0.3 degrees Celsius reduces production by -0.09 percent, while a shock of 1 degree Celsius would reduce economic activity by -0.37 percent. In turn, controlling for network linkages across states amplifies the negative macroeconomic effects of weather fluctuations. This model estimates an aggregate impact of around -0.10 percent for the small shock and a contraction of about 1.14 percent for the large shock.

As weather fluctuations increase, the network effect becomes more relevant, explaining over 70% of the aggregate impact for fluctuations larger than 0.32 degrees Celsius. As mentioned earlier, including production networks indirectly exposes states to weather fluctuations from other regions. To assess the relevance of this channel at an aggregate level, I separated the overall impact of weather fluctuations into the direct and network effects. Figure ddisplays these shares for weather fluctuations exceeding 0.15 degrees Celsius. At this point, both components start exhibiting negative effects. The direct exposure explains close to 80 percent of the aggregate effect for smaller shocks, but this percentage reduces drastically as weather fluctuations increase. For example, it reaches around 30 percent for fluctuations close to 0.32 Celsius degree, and around 11 percent for fluctuations close to 1 Celsius. Differences compared to the state-level analysis in Figure 12 are because direct effects can be either positive or negative, and many cancel out during the aggregation process.

To test the robustness of these conclusions, I calculated the estimates of the theoretical models in sections 3 and 4 using a total of eight different versions of their empirical counterparts. The first set of alternative models changes the choice of the temperature indicator τ from average temperatures to maximum and minimum temperatures. A second set of models varies the length of the rolling windows from which I compute the reference base $\bar{\tau}_{g,m,t}$, changing it to 5, 20, and 30 years in each case. The final set of alternative models uses a different measure of economic activity. One of the concerns results from my choice of using state-specific consumer prices as deflators to construct the real GDP by state instead of using sector-specific price indices. Using the sector-state price index is the closest approximation to the theoretical model. However, this level of disaggregation is not available for the same horizon as my empirical exercise. I present

Figure 15. Share of direct effect to aggregate impact of weather fluctuations



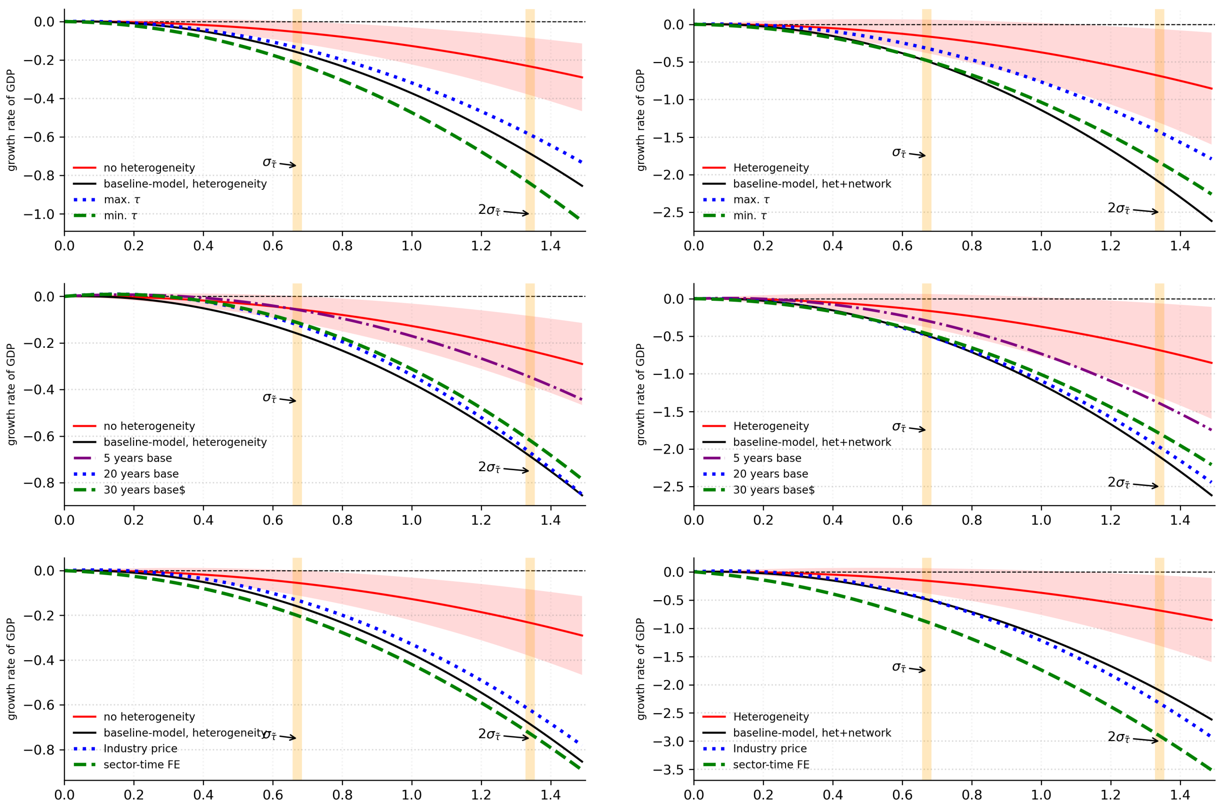
two approaches that partially allow me to handle this issue. The first approach is using the aggregate deflator of the value-added by industry provided by the BEA and applying the same weights and process to chain them due to the change in the classification system described in section 3. The second approach is to change the specification of my baseline models to include a sector-time fixed effect to control for any common sector-specific shock that could be an aggregate change in prices.

The results from the sensitivity analysis show my conclusions are robust to different choices of temperature indicators and measurements of economic activity. Figure 16 plots this comparison. The left panel of this figure compares the model from section 3 plotted as solid black lines with the aforementioned specifications. The right panel compares the results from these alternative models with the baseline model with heterogeneity and networks presented in section 4. To ease the comparison, reference points were plotted in red with a one-standard deviation confidence interval. The reference point chosen for the models in panel (a) was the regression without heterogeneities or networks, while the baseline model from section 4 was selected as a reference for plots in panel (b). Results from the alternative models were plotted as dotted blue lines, dashed green lines, and dashed purple lines. In every case, we can see that the results from the alternative models do not separate drastically from the baseline estimations and do not change my

Figure 16. Macroeconomic effect of $\tilde{\tau}$ under alternatives models

(a) Models with Heterogeneity

(b) Models with Heterogeneity and Networks



Note: Plots in the left panel show the comparison respect to the model from section 3 while the right panel presents the comparison respect to the model with heterogeneities and networks. The results from the baseline estimation are plotted as solid black lines. Plots at the top show the results from the models with a different temperature indicator, plots in the middle present the impact estimated by changing the window length, and the plots at the bottom display the results from the models to handle concerns regarding sectoral prices. In every picture, a reference for comparison is plotted in red in addition to a one-standard-deviation confidence interval. The model without heterogeneity was chosen as a reference for the model with heterogeneity. Finally, the results from the model with heterogeneity were chosen as a reference for the pictures in the right panel.

conclusions. Additional plots are added in appendix B

6 Including non-economic connections

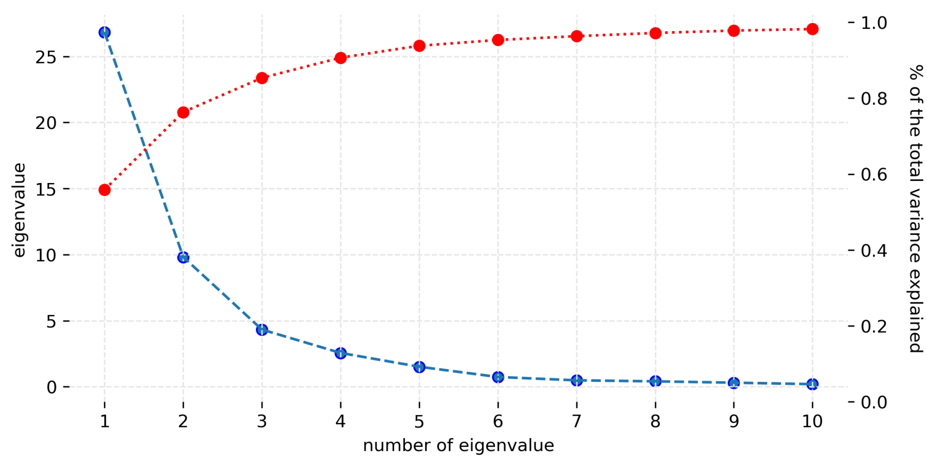
One potential concern that may arise about the counterfactual scenarios proposed in sections 3 and 4 is the likelihood of a widespread temperature increase across the United States. To address it, I present an additional counterfactual exercise based on a common factor analysis. In this new scenario, I find the underlying components that explain the largest fraction of the variance of the temperature anomalies. Once these components are identified, I proceed to perturbate each common factor by a shock equal to one standard deviation. As a result, I have a new set of simulated temperature anomalies $\{\tilde{\tau}_n^{sim}\}$ that I can use to follow the counterfactual strategy in section 4. This approach emerges naturally since the NOAA recognizes nine climate regions across the country, meaning that some temperature anomalies could have a common source. Moreover, the presence of common factors does not alter my previous estimates since they only affect the economy through temperature changes.

To simplify the analysis, I assume that the common factors affect temperature anomalies linearly as follows:

$$\tilde{\tau}_{nt} = \Lambda \tau_t^k + \epsilon_{\tilde{\tau},nt} \tag{35}$$

where τ_t^k is a vector of k unobservable common factors, and Λ is a loading matrix. To estimate Λ, I use principal component analysis, which involves calculating the eigenvalue-eigenvector decomposition and choosing the eigenvectors associated with the k largest eigenvalues as loadings.

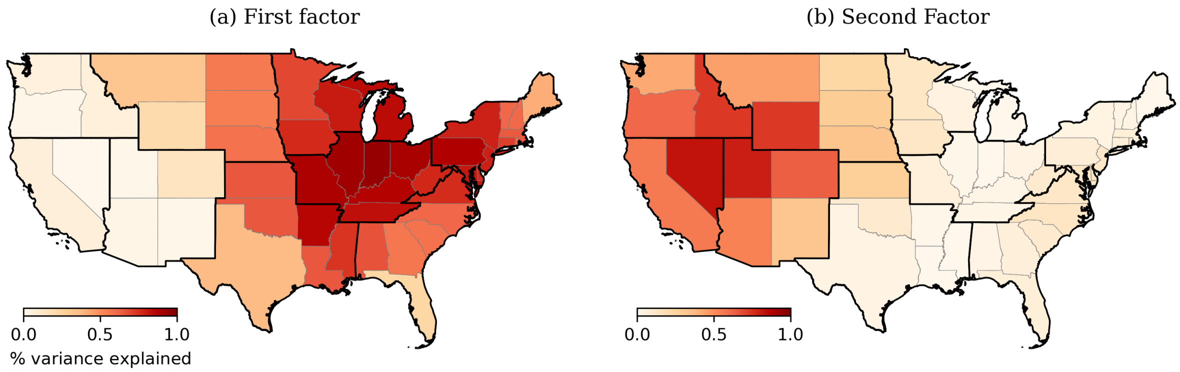
Figure 17. Factor analysis of weather fluctuations



Note: The figure shows the share of the cumulative variance explained by the k-largest eigenvalue (red line, right-axis) and the value of the eigenvalues (blue line, left axis). The share in cumulative variance was calculated as the average across states.

Based on a graphical analysis and the average variance explained by each factor, I choose $k = 2$ components as representative of the whole sample. Figure 17 displays the values of the 10 largest eigenvalues as a blue line and the cumulative variance explained by adding a new factor in red. The blue line becomes nearly flat after the fifth factor, indicating that subsequent factors have limited explanatory power. In fact, the first two components alone explain roughly 80 percent of the total variance. Moreover, their geographic distribution depicted in Figure 18 suggests that they are the underlying components associated with the east and west zones of the country. Given these two observations, I chose two factors[13] for the counterfactual analysis.

Figure 18. Contribution to $\sigma^2_{\tilde{\tau}}$ by state



Note: Maps plot the contribution of the first two common factors to the variance of $\tilde{\tau}$ by state. The intensity of the color reflects the relevance of the factor over a particular state.

My estimates suggest that a shock of one standard deviation[14] in the common component reduces the economic activity in 27 out of 48 states and 14 out of 20 industries. At the state level, the largest contractions are observed in New Jersey (-1.25%) and Lousiana (-0.85%) as reported by Figure 27 in the appendix. At the industry level, the contraction in agriculture (-0.98%), utilities (-0.64%), and real estate (-0.54%) would be the most pronounced (see Figure 28 of the appendix). At the aggregate level, these results lead to a contraction of economic activity close to -0.31 percent (with a standard deviation of 0.22). To compare this result with respect to the previous models, I expressed those estimates in terms of standard deviations of $\tilde{\tau}$ and plotted them in Figure 19. This comparison shows that the negative impact of the shock in the common factors is not as accentuated as in the case of a generalized increase in temperature but is still sizable.

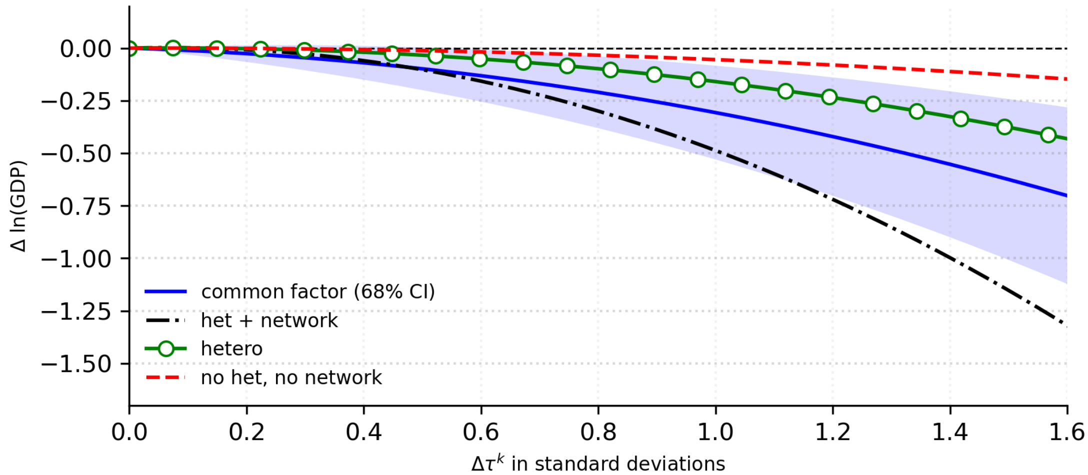
7 Concluding remarks

Introducing sector-state heterogeneous sensitivities of productivity to weather fluctuations amplifies the negative effect of a sudden temperature increase. I found that when both mechanisms are included, the economic activity decreases by 1.14 percent, while when both are mute, a similar anomaly in temperature contracts the economy by 0.13

[13]The loading factors Λ and the specific changes in temperature by state are reported in Table 5

[14]The signs of the shocks have been normalized to generate -on average- an increase in temperature

Figure 19. Impact of a shock in τ_t^k on economic activity



Note: The solid blue line shows the aggregate impact of a shock in the two common factors. The shocks are defined in terms of standard deviation. The dashed black line displays the effect of a generalized temperature increase from the model with heterogeneity and production networks. The green line with markers plots the results from the model with only heterogeneity, while the red dashed line reports the estimates from the model without any of these characteristics. The responses of the last three lines were computed in terms of standard deviation of $\tilde{\tau}$ to ease the comparability.

percent. A simple decomposition shows that the estimated heterogeneity across states is mostly driven by geographical conditions rather than differences in their sectoral composition. These findings show the relevance of state-specific policies oriented to tackle these differences. However, as temperature shocks become larger, their impact on the economy -per unit Celsius- not only intensifies but also spreads significantly, suggesting a role for common policies. This is true even in not extreme cases, as revealed by a common factor analysis.

The simplicity and flexibility of my approach, in conjunction with using a long horizon data in production and the short-run scope, are keystones in my analysis. Although a specific general equilibrium model initially inspired my estimations, their results still apply to various structures. However, the presence of market inefficiencies can alter my estimates, and their inclusion is a future source of research.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The Network Origins of Aggregate Fluctuations." *Econometrica*, 80(5): 1977–2016.

Acevedo, Sebastian, Mico Mrkaic, Natalija Novta, Evgenia Pugacheva, and Petia Topalova. 2020. "The Effects of Weather Shocks on Economic Activity: What are the Channels of Impact?" *Journal of Macroeconomics*, 65: 103207.

Baqaee, David Rezza, and Emmanuel Farhi. 2019. "The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem." *Econometrica*, 87(4): 1155–1203.

Baqaee, David Rezza, and Emmanuel Farhi. 2020. "Productivity and misallocation in general equilibrium." *The Quarterly Journal of Economics*, 135(1): 105–163.

Barrot, Jean-Noël; Sauvagnat, Julien. 2016. "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks *." *The Quarterly Journal of Economics*, 131(3): 1543–1592.

Bigio, Saki, and Jennifer La'o. 2020. "Distortions in production networks." *The Quarterly Journal of Economics*, 135(4): 2187–2253.

Bilal, Adrien, and Esteban Rossi-Hansberg. 2023. "Anticipating Climate Change Across the United States." National Bureau of Economic Research.

Burke, Marshall, Solomon M. Hsiang, and Edward Miguel. 2015. "Global non-linear effect of temperature on economic production." *Nature*, 527(7577): 235–239.

Caliendo, Lorenzo, Fernando Parro, Esteban Rossi-Hansberg, and Pierre-Daniel Sarte. 2018. "The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy." *The Review of Economic Studies*, 85(4): 2042–2096.

Carvalho, Vasco. 2007. "Aggregate fluctuations and the network structure of intersectoral trade." Department of Economics and Business, Universitat Pompeu Fabra Economics Working Papers 1206.

Carvalho, Vasco M, and Alireza Tahbaz-Salehi. 2019. "Production networks: A primer." *Annual Review of Economics*, 11: 635–663.

Colacito, Riccardo, Bridget Hoffmann, and Toanma Phan. 2018. "Temperature and Growth: A Panel Analysis of the United States." *Journal of Money, Credit and Banking*, 51(2-3): 313–368.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics*, 4(3): 66–95.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature*, 52(3): 740–798.

Donadelli, M., M. Jüppner, M. Riedel, and C. Schlag. 2017. "Temperature shocks and welfare costs." *Journal of Economic Dynamics and Control*, 82: 331–355.

Dushnitsky, Gary, and Sayan Sarkar. 2022. "Here comes the sun: The impact of incidental contextual factors on entrepreneurial resource acquisition." *Academy of Management Journal*, 65(1): 66–92.

Gabaix, Xavier. 2011. "The granular origins of aggregate fluctuations." *Econometrica*, 79(3): 733–772.

Hancock, Peter A, Jennifer M Ross, and James L Szalma. 2007. "A meta-analysis of performance response under thermal stressors." *Human factors*, 49(5): 851–877.

Hennessy, K., and J. Lawrence. 2022. "IPCC sixth assessment report (AR6): climate change 2022-impacts, adaptation and vulnerability: regional factsheet Australasia."

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, Kate Larsen, and Trevor Houser. 2017. "Estimating economic damage from climate change in the United States." *Science*, 356(6345): 1362–1369.

Leduc, Sylvain, and Daniel J Wilson. 2023. "Climate Change and the Geography of the US Economy."

Lerner, Josh, and Antoinette Schoar. 2004. "The illiquidity puzzle: theory and evidence from private equity." *Journal of Financial Economics*, 72(1): 3–40.

Rudik, Ivan, Gary Lyn, Weiliang Tan, and Ariel Ortiz-Bobea. 2022. "The economic effects of climate change in dynamic spatial equilibrium."

Yuskavage, Robert E, et al. 2007. "Converting historical industry time series data from SIC to NAICS." Washington, DC US Department of Commerce, Bureau of Economic Analysis.

Appendix A Data

In this appendix, I present the data sources used for my analysis and describe how I process them.

A.1 Economic data at geographical level

I obtained the data of economic activity from the Bureau of Economic Analysis (BEA) historical statistic. They report national account statistics by various levels of geographical disaggregation such as County level and Metropolitan Statistical Areas (MSAs) since 2001 and State level since 1963 in nominal values and 1977 in real terms. To cover the largest possible horizon, I preferred to use state-level data at nominal value. Due to weather-related data limitations, I don't include the District of Columbia in the analysis. I also exclude Alaska and Hawaii since I focus my attention on the contiguous United States. Therefore, I have 48 states in my dataset. Then, I excluded the sectors associated with government activities, keeping a total of 59 sectors.

To overcome the change in the classification system from the Standard Industrial Classification to the North American Industry Classification System (NAICS) in 1997, I followed Yuskavage et al. (2007), who developed concordance tables that allowed me to chain both datasets. Those tables can be downloaded from the BEA website. The Excel file comprises one concordance table for the interval 1947-1987 but several from the period 1987-1997. In the last case, I use the table associated with the Gross Domestic Output accounts (sheet VA). This process gives me three different tables expressed in the NAIC system that overlap at the end and start of the sample. For example, before the chaining, I had the year 1997 in two different datasets. One with information on production between 1997 and 2021 and another covering 1987-1997. Then, to avoid any problem related to a different nominal value in the overlapping years, I chained these tables using gross ratios of the overlapping year. Table 1 exemplifies this process.

After chaining both tables, I convert the nominal GDP into real terms by deflating them using state-specific consumer price indices. Studies commonly use the aggregate consumer price index (CPI) as a deflator to isolate real fluctuations from price movements. However, the particularities of each state such as different consumer basket structures or state-specific demand shocks could cause discrepancies between the state-specific price fluctuations and the national measurement. For example, during local disasters, equilib-

Table 1. Chaining SIC-based accounts and NAIC-based accounts

	Before chaining			Gross ratio	After chaining	
	Table 1	Table 2				
	1997	1997	1998		1997	1998
NAIC 1	100	101	105	1.01	100.0	104.0
NAIC 2	99	102	104	1.03	99.0	100.9

rium prices at the state would fluctuate more than the national ones, making the CPI no longer a good proxy for real movements for that state. To mitigate these possible problems, I use the series of price indexes by Metropolitan Statistical Area (MSA) and Regional Division calculated by the Bureau of Labor Statistics. This dataset comprises consumer price indexes for 21 MSAs and four regions. While the regional CPI started in 1966, the initial point differs across MSAs, with some starting in 1914 but others late in 2002. Table 2 shows the list of MSAs and regions from which BLS has records about specific CPIs and their starting dates.

Table 2. List of Metropolitan Statistical Areas and Regions (BLS)

Code Variable at BLS Code 1	Code Variable at BLS Code 2	Name	Full Name	Type	Initial period
CUUR0100SA0	CUUS0100SA0	Northeast	Northeast	Region	1966
CUUR0400SA0	CUUS0400SA0	West	West		
CUUR0200SA0	CUUS0200SA0	Midwest	Midwest		
CUUR0300SA0	CUUS0300SA0	South	South		
CUURS35CSA0	CUUSS35CSA0	Atlanta	Atlanta-Sandy Springs-Roswell, GA	Metropolitan Statistical Area	1917
CUURS35ESA0	CUUSS35ESA0	Baltimore	Baltimore-Columbia-Towson, MD		1914
CUURS11ASA0	CUUSS11ASA0	Boston	Boston-Cambridge-Newton, MA-NH		1914
CUURS23ASA0	CUUSS23ASA0	Chicago	Chicago-Naperville-Elgin, IL-IN-WI		1914
CUURS37ASA0	CUUSS37ASA0	Dallas	Dallas-Fort Worth-Arlington, TX		1963
CUURS48BSA0	CUUSS48BSA0	Denver	Denver-Aurora-Lakewood, CO		1964
CUURS23BSA0	CUUSS23BSA0	Detroit	Detroit-Warren-Dearborn, MI		1914
CUURS37BSA0	CUUSS37BSA0	Houston	Houston-The Woodlands-Sugar Land, TX		1914
CUURS49ASA0	CUUSS49ASA0	Los Angeles	Los Angeles-Long Beach-Anaheim, CA		1914
CUURS35BSA0	CUUSS35BSA0	Miami	Miami-Fort Lauderdale-West Palm Beach, FL		1977
CUURS24ASA0	CUUSS24ASA0	Minneapolis	Minneapolis-St.Paul-Bloomington, MN-WI		1917
CUURS12ASA0	CUUSS12ASA0	New York	New York-Newark-Jersey City, NY-NJ-PA		1914
CUURS12BSA0	CUUSS12BSA0	Philadelphia	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD		1914
CUURS48ASA0	CUUSS48ASA0	Phoenix	Phoenix-Mesa-Scottsdale, AZ		2002
CUURS49CSA0	CUUSS49CSA0	Riverside	Riverside-San Bernardino-Ontario, CA		2017
CUURS24BSA0	CUUSS24BSA0	St. Louis	St. Louis, MO-IL		1917
CUURS49ESA0	CUUSS49ESA0	San Diego	San Diego-Carlsbad, CA		1965
CUURS49BSA0	CUUSS49BSA0	San Francisco	San Francisco-Oakland-Hayward, CA		1914
CUURS49DSA0	CUUSS49DSA0	Seattle	Seattle-Tacoma-Bellevue WA		1914
CUURS35DSA0	CUUSS35DSA0	Tampa	Tampa-St. Petersburg-Clearwater, FL		1987
CUURS35ASA0	CUUSS35ASA0	Washington	Washington-Arlington-Alexandria, DC-VA-MD-WV		1914

Note: The table reports the list of Statistical Regions and Metropolitan Statistical Areas that the BLS uses to compute geographically specific Consumer Price Indexes. In addition, I report the name of the series associated with each CPI and the full name of the MSAs.
Source: Bureau of Labor Statistics

Some MSAs cover multiple states, while others include two or more MSAs. Then, I follow the next strategy to assign disaggregated CPIs geographically[15]:

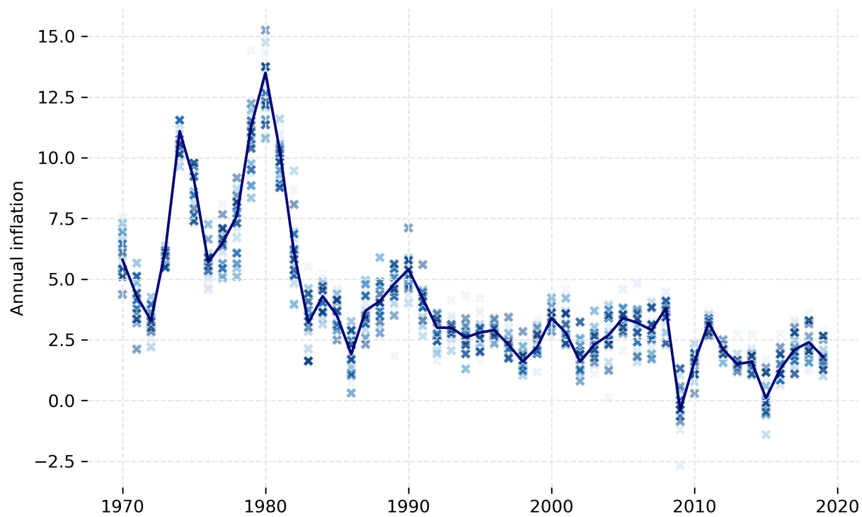
1. If none of the MSA in the list is situated in the specific state, then the regional CPI is chosen.
2. Then, when only one MSA is located in the specific state, the MSA's CPI is picked.

[15] A more detailed structure for the MSAs related to each state can be found in the Excel file called 'tablemetro.xlsx'.

3. If multiple MSAs are included in a state, the state's CPI is computed as the average of the MSA's CPIs

Figure 20 shows the evolution of the computed state-specific CPI inflation plotted in markers and the CPI inflation for the whole United States from 1970 to 2019. We can appreciate the presence of some significant differences giving us a sense of the relevance of including MSAs and regional CPIs in any state-based calculation.

Figure 20. Inflation of the CPI by state



Note: Figure shows the evolution of CPI inflation by state (in markers) in comparison to aggregate inflation (solid blue line). The aggregate CPI inflation was obtained from the Federal Reserve Bank of Minneapolis.

The growth rate of the real GDP per capita is calculated by taking the first log difference and subtracting the population growth rate. Estimates of the population at the state level were obtained from the Federal Reserve Bank of Saint Louis. They provide annual estimates based on the information released by the United States Census Bureau. Table 3 shows summary statistics of the growth rate of the GDP per capita at the state level since 1970, using two different methods of calculation. Column "Aggregate" presents the average growth rate computed from the aggregate statistics of the state, while the column "Sector-based" reports the results when the individual growth rate by sector-state is aggregate using share in nominal state's GDP as weigh. There are not significance differences between both results indicating that the level of dissagregation used in my analysis gives sensible results.

Table 3. Growth rate per capita by state

State	Aggregate mean	Aggregate std	Sector-based mean	Sector-based std	State	Aggregate mean	Aggregate std	Sector-based mean	Sector-based std
Alabama	1.43	3.28	1.49	3.14	Nebraska	1.91	3.58	1.86	3.78
Arizona	1.23	4.23	1.11	4.21	Nevada	0.86	4.02	0.75	3.84
Arkansas	1.33	3.41	1.44	3.48	New Hampshire	1.74	3.49	1.74	3.50
California	1.15	2.89	1.17	2.86	New Jersey	1.38	2.68	1.39	2.55
Colorado	1.61	2.91	1.52	2.92	New Mexico	1.19	3.72	1.14	4.18
Connecticut	1.72	3.21	1.62	3.48	New York	1.35	2.76	1.39	2.83
Delaware	1.62	5.29	1.52	4.64	North Carolina	1.34	3.68	1.42	3.67
Florida	1.26	3.64	1.17	3.59	North Dakota	3.13	7.44	3.13	9.17
Georgia	1.70	3.54	1.73	3.62	Ohio	1.20	3.44	1.23	3.45
Idaho	1.33	3.98	1.06	4.09	Oklahoma	1.60	4.49	1.62	4.86
Illinois	1.42	2.86	1.36	3.04	Oregon	1.12	3.75	1.12	4.17
Indiana	1.19	4.33	1.20	4.22	Pennsylvania	1.36	2.23	1.36	2.32
Iowa	1.72	4.02	1.71	4.40	Rhode Island	1.26	2.77	1.37	2.88
Kansas	1.67	2.66	1.73	2.98	South Carolina	1.53	3.73	1.61	3.67
Kentucky	1.12	3.26	1.07	3.21	South Dakota	2.71	4.64	2.61	5.51
Louisiana	1.19	4.88	1.29	4.91	Tennessee	1.65	3.60	1.70	3.61
Maine	1.40	2.92	1.47	3.02	Texas	1.86	3.45	1.95	3.60
Maryland	1.72	2.71	1.78	2.73	Utah	1.76	3.24	1.76	3.36
Massachusetts	1.74	3.00	1.76	2.99	Vermont	1.22	3.29	1.23	3.21
Michigan	0.85	5.27	0.81	5.46	Virginia	1.72	2.79	1.72	2.76
Minnesota	1.49	3.26	1.46	3.50	Washington	1.20	3.29	1.32	3.53
Mississippi	1.24	3.46	1.26	3.42	West Virginia	1.05	3.12	1.11	3.15
Missouri	1.19	3.13	1.22	3.36	Wisconsin	1.40	3.14	1.41	3.22
Montana	1.17	3.95	1.04	4.46	Wyoming	1.37	7.31	1.56	7.74

Note: The table shows the average growth rate of the GDP per capita by state and its standard deviations. The results below the column "Aggregate" were computed using the aggregate real GDP at the state level. Results below the column "Sector-Based" compute the average growth rate as the weighted average of the sector's growth rates using the share in nominal GDP as weigh. The growth rate was approximated by the first log difference.

Table 4. List of sector present in the estimation sample

NAIC	Sector	Industry	Tradable	NAIC	Sector	Industry	Tradable
721	Accommodation	Accomodation	N	315	Apparel, leather, and allied product manufactu...	Manuf. Nondurable	Y
722	Food services and drinking places	Accomodation	N	325	Chemical manufacturing	Manuf. Nondurable	Y
561	Administrative and support services	Admin support	N	311	Food and beverage and tobacco product manufact...	Manuf. Nondurable	Y
562	Waste management and remediation services	Admin support	N	322	Paper manufacturing	Manuf. Nondurable	Y
111	Farms	Agriculture	N	324	Petroleum and coal products manufacturing	Manuf. Nondurable	Y
113	Forestry, fishing, and related activities	Agriculture	N	326	Plastics and rubber products manufacturing	Manuf. Nondurable	Y
23	Construction	Construction	N	323	Printing and related support activities	Manuf. Nondurable	Y
61	Educational services	Education serv.	N	313	Textile mills and textile product mills	Manuf. Nondurable	Y
713	Amusement, gambling, and recreation industries	Entertainment	N	212	Mining (except oil and gas)	Mining	Y
711	Performing arts, spectator sports, museums, an...	Entertainment	N	211	Oil and gas extraction	Mining	N
525	Funds, trusts, and other financial vehicles	Finance	N	213	Support activities for mining	Mining	N
524	Insurance carriers and related activities	Finance	N	81	Other services	Others	N
521	Monetary Authorities- central bank, credit int...	Finance	N	54	Professional, scientific, and technical services	Prof. services	N
523	Securities, commodity contracts, and other fin...	Finance	N	531	Real estate	Real estate	N
621	Ambulatory health care services	Health care	N	532	Rental and leasing services and lessors of non...	Real estate	N
622	Hospitals and Nursing and residential care fac...	Health care	N	44	Retail trade	Retail trade	Y
624	Social assistance	Health care	N	481	Air transportation	Transportation	N
515	Broadcasting (except Internet) and telecommuni...	Information	N	487	Other transportation and support activities	Transportation	N
518	Data processing, hosting, and other informatio...	Information	N	486	Pipeline transportation	Transportation	N
512	Motion picture and sound recording industries	Information	N	482	Rail transportation	Transportation	N
511	Publishing industries (except Internet)	Information	Y	485	Transit and ground passenger transportation	Transportation	N
55	Management of companies and enterprises	Management	Y	484	Truck transportation	Transportation	N
334	Computer and electronic product manufacturing	Manuf. Durable	Y	493	Warehousing and storage	Transportation	Y
335	Electrical equipment, appliance, and component...	Manuf. Durable	Y	483	Water transportation	Transportation	N
332	Fabricated metal product manufacturing	Manuf. Durable	Y	22	Utilities	Utilities	N
337	Furniture and related product manufacturing	Manuf. Durable	Y	42	Wholesale trade	Wholesale trade	Y
333	Machinery manufacturing	Manuf. Durable	Y				
339	Miscellaneous manufacturing	Manuf. Durable	Y				
3361	Motor vehicles, bodies and trailers, and parts...	Manuf. Durable	Y				
327	Nonmetallic mineral product manufacturing	Manuf. Durable	Y				
3364	Other transportation equipment manufacturing	Manuf. Durable	N				
331	Primary metal manufacturing	Manuf. Durable	Y				
321	Wood product manufacturing	Manuf. Durable	Y				

Note: Some of the NAIC are not equal to the reported in the national accounts due to I recoded them as a number, usually taking of the NAICs code as reference. The classification of tradable and non tradable was based in the CFS tables that report interregional trading

A.1.1 List of tradable and nontradable sectors

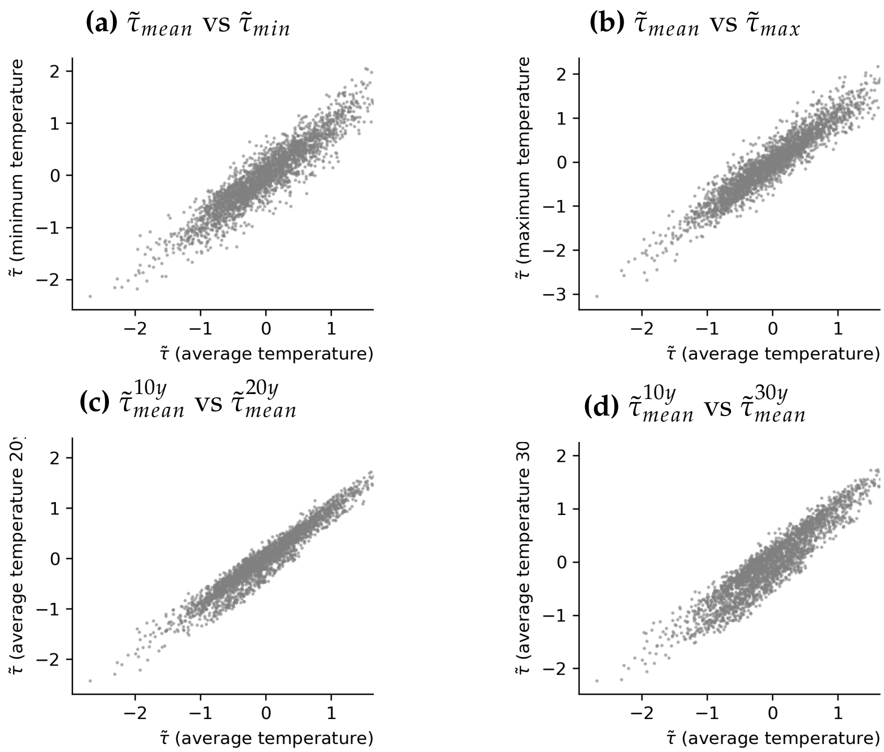
Although the estimations were made at the sector level, results are presented at the industry level to ease the presentation. Table 4 shows the list of the considered sectors, their industry, and whether they are treated as tradable or nontradable based on the CFS tables.

A.2 Weather variables

The variables related to weather conditions were obtained from the National Oceanic and Atmospheric Administration. The routines of downloading and processing are in the files "dataweather.do" and "dataweather_county.do". Since the scope of this study lies in analyzing the short and medium-run effects of weather fluctuations, I prefer to use temperature anomalies ($\tilde{\tau}_{s,t,h}$) instead of absolute levels. I define a temperature anomaly as the difference between a temperature indicator ($\tau_{s,t}$) and a reference point ($\bar{\tau}_{s,t}^{(h)}$). In the main text, the considered temperature indicator was the average temperature and the reference point was the rolling average of these temperatures in a 10-year window. Regarding the latter, the World Meteorological Organization (WMO) recommends using the 30-year window average and changing it every decade[16] to describe a climate normal. Although this bin size can capture the evolution [and fluctuations] of climate conditions, it is less sensible, from an economic perspective, when agents try to anticipate future conditions before taking their best actions. Therefore, I use a shorter span to define the reference point. In particular, I choose a ten-year window to match the average investment plan's horizon of general partners investors (GP) as is shown by Lerner and Schoar (2004). On the other hand, the choice of using average temperatures might raise concerns about how representative they are in comparison to minimum or maximum temperatures. In figure 21, I plot a set of scatterplots that show the relation between the temperature anomalies used in the main results and other proxies of weather fluctuations. The alternative measures of weather anomalies in panels (a) and (b) were calculated using minimum and maximum temperature as indicators and a window of 10 years as the reference point. In the case of panels (c) and (d), I change the reference point to be 20-year window and 30-year window, respectively. In all the cases, we see a close relationship characterized by a correlation coefficient larger than 0.9. These exploratory results suggest that the choice of the temperature indicator would affect the conclusions of the paper.

[16]For example, the average temperature from 1980-2010 is the reference base for temperatures in 2015

Figure 21. Relation between temperature anomalies indicators



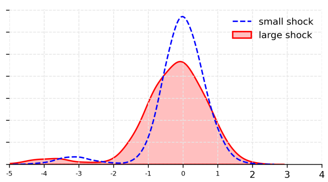
(a) $\tilde{\tau}_{mean}$ vs $\tilde{\tau}_{min}$ **(b)** $\tilde{\tau}_{mean}$ vs $\tilde{\tau}_{max}$ **(c)** $\tilde{\tau}^{10y}_{mean}$ vs $\tilde{\tau}^{20y}_{mean}$ **(d)** $\tilde{\tau}^{10y}_{mean}$ vs $\tilde{\tau}^{30y}_{mean}$

Note: Each panel depicts a scatterplot between temperature anomalies in the average temperature and other proxies for weather anomalies.

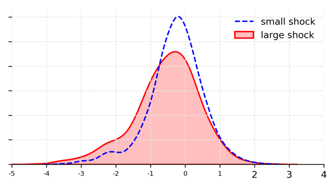
Appendix B Sensitivity analysis, additional figures

Figure 22. Distribution of $\mathcal{G}_{lg}(\tilde{\tau}^{o})$, alternative models for **heterogeneous** responses

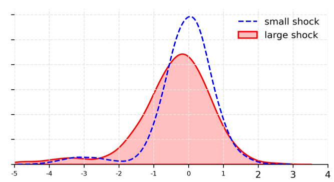
(a) max τ



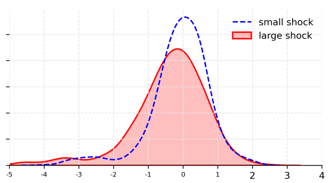
(b) min τ



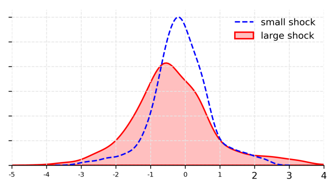
(c) 20-year τ



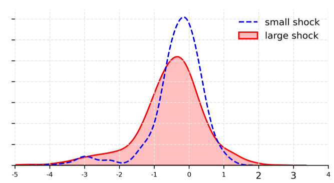
(d) 30-year τ



(e) Sectoral Price



(f) Sector-time FE



(g) 5-year reference

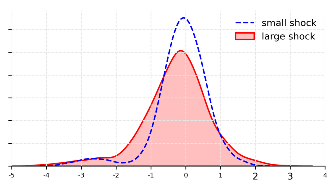


Figure 23. Aggregate effect of $\tilde{\tau}$, alternative models for **heterogeneous** responses

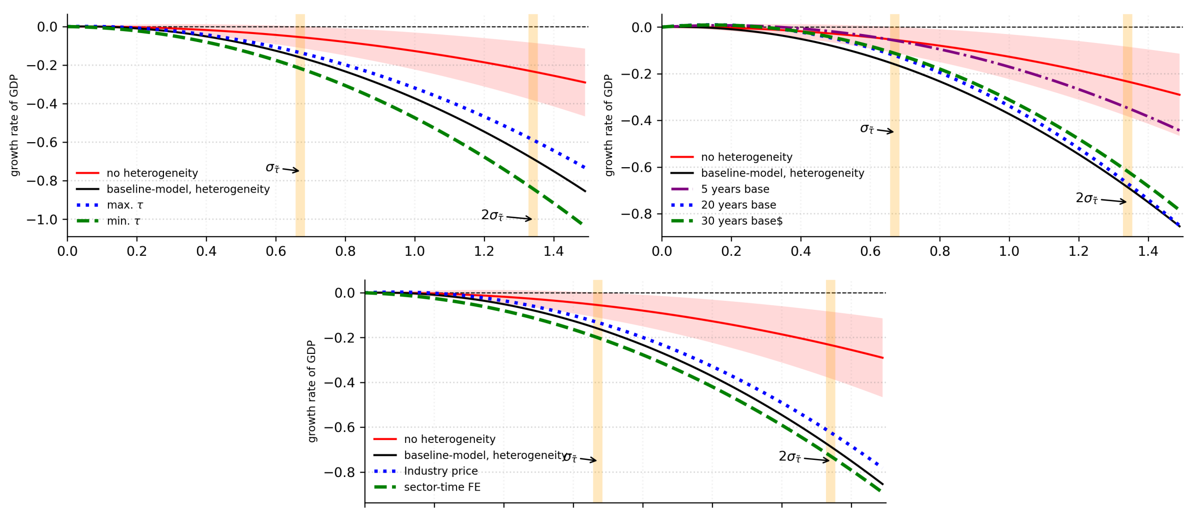
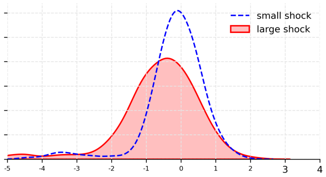
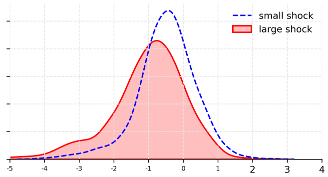


Figure 24. Distribution of $\mathcal{G}_{lg}(\tilde{\tau}^{o})$, alternative models for **networks** responses

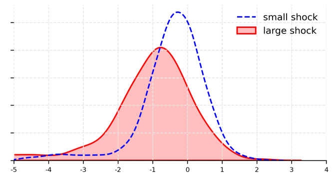
(a) max τ



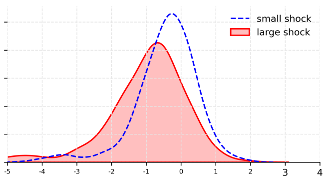
(b) min τ



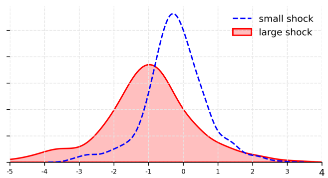
(c) 20-year τ



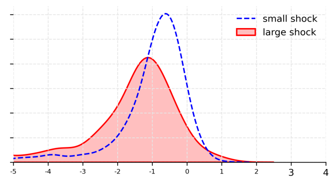
(d) 30-year τ



(e) Sectoral Price



(f) Sector-time FE



(g) 5-years reference

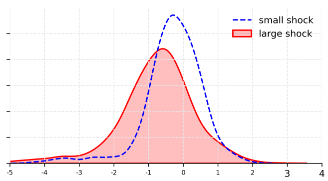
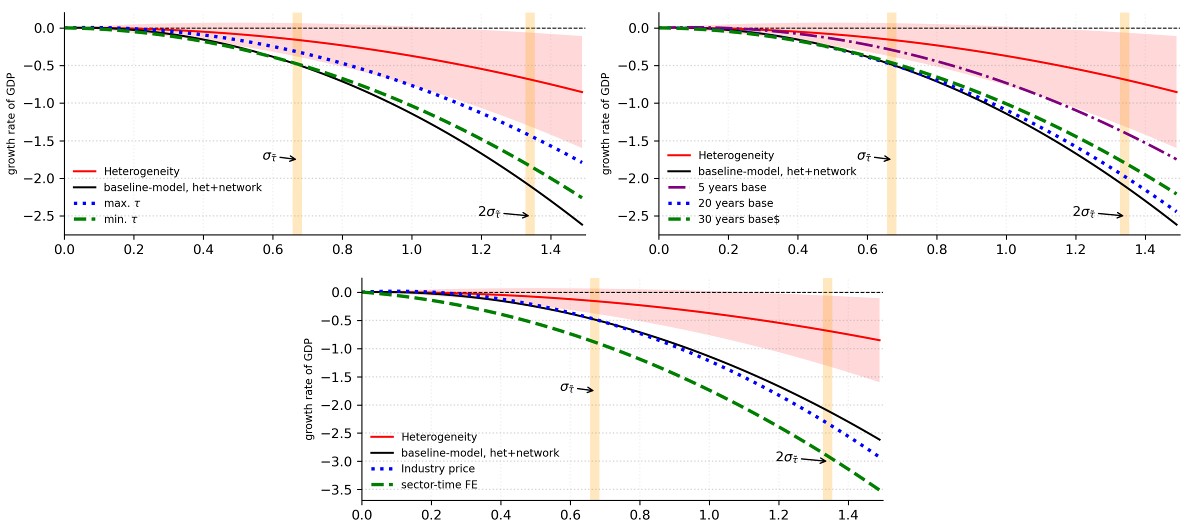


Figure 25. Aggregate effect of $\tilde{\tau}$, alternative models for **networks**



Appendix C Loading Factors

Table 5. Loading factors and total change in temperature

state	Λ_1	Λ_2	$\Delta\tilde{\tau}$	state	Λ_1	Λ_2	$\Delta\tilde{\tau}$
AL	-0.82	-0.16	0.51	NC	-0.78	-0.37	0.61
AR	-0.93	0.11	0.51	ND	-0.75	0.48	0.31
AZ	0.14	0.73	-0.41	NE	-0.76	0.57	0.16
CA	0.26	0.75	-0.49	NH	-0.78	-0.17	0.62
CO	-0.39	0.80	-0.23	NJ	-0.89	-0.36	0.73
CT	-0.84	-0.27	0.67	NM	-0.11	0.56	-0.21
DE	-0.87	-0.39	0.71	NV	0.02	0.91	-0.53
FL	-0.48	-0.26	0.36	NY	-0.89	-0.19	0.73
GA	-0.75	-0.26	0.54	OH	-0.95	-0.18	0.81
IA	-0.88	0.36	0.49	OK	-0.81	0.32	0.30
ID	-0.24	0.85	-0.41	OR	-0.09	0.79	-0.39
IL	-0.96	0.10	0.69	PA	-0.94	-0.28	0.77
IN	-0.97	-0.07	0.78	RI	-0.79	-0.32	0.63
KS	-0.81	0.52	0.21	SC	-0.76	-0.32	0.58
KY	-0.93	-0.15	0.69	SD	-0.74	0.54	0.22
LA	-0.81	-0.04	0.43	TN	-0.91	-0.13	0.62
MA	-0.81	-0.27	0.64	TX	-0.61	0.17	0.21
MD	-0.90	-0.37	0.73	UT	-0.10	0.89	-0.51
ME	-0.64	-0.07	0.49	VA	-0.87	-0.36	0.66
MI	-0.92	0.03	0.77	VT	-0.79	-0.17	0.66
MN	-0.83	0.36	0.51	WA	-0.23	0.65	-0.25
MO	-0.94	0.24	0.53	WI	-0.90	0.22	0.66
MS	-0.86	-0.04	0.48	WV	-0.88	-0.32	0.72
MT	-0.56	0.67	-0.10	WY	-0.45	0.85	-0.29

Figure 26. Contribution to $\sigma^2_{\tilde{\tau}}$ by state

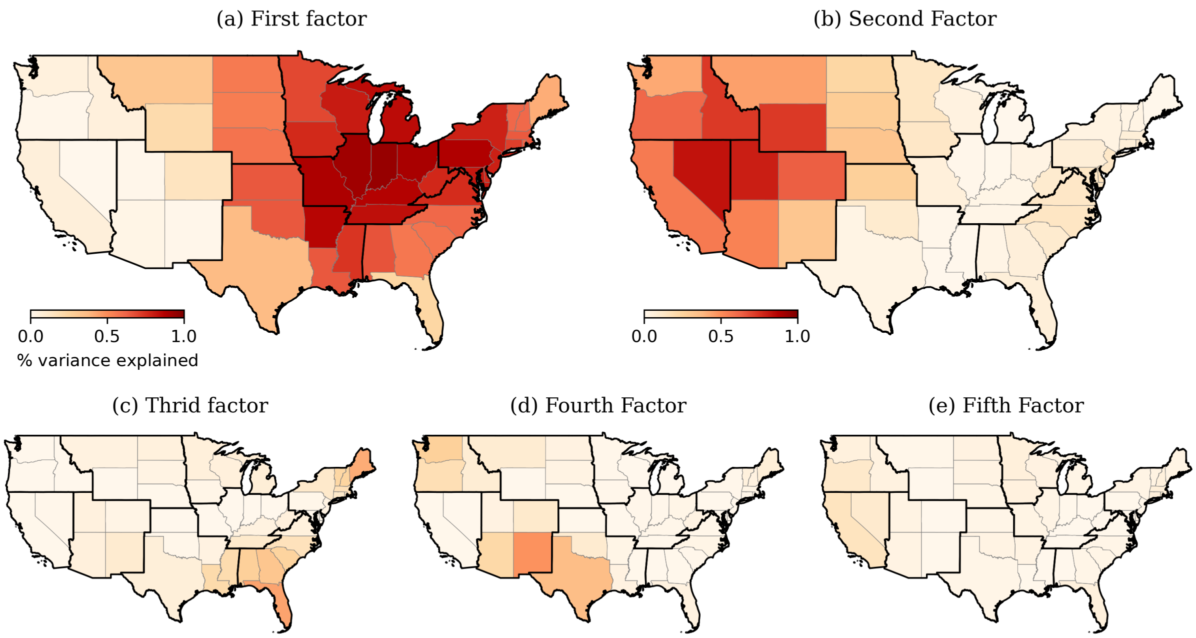


Figure 27. Impact of a shock in τ_t^k on economic activity, by state

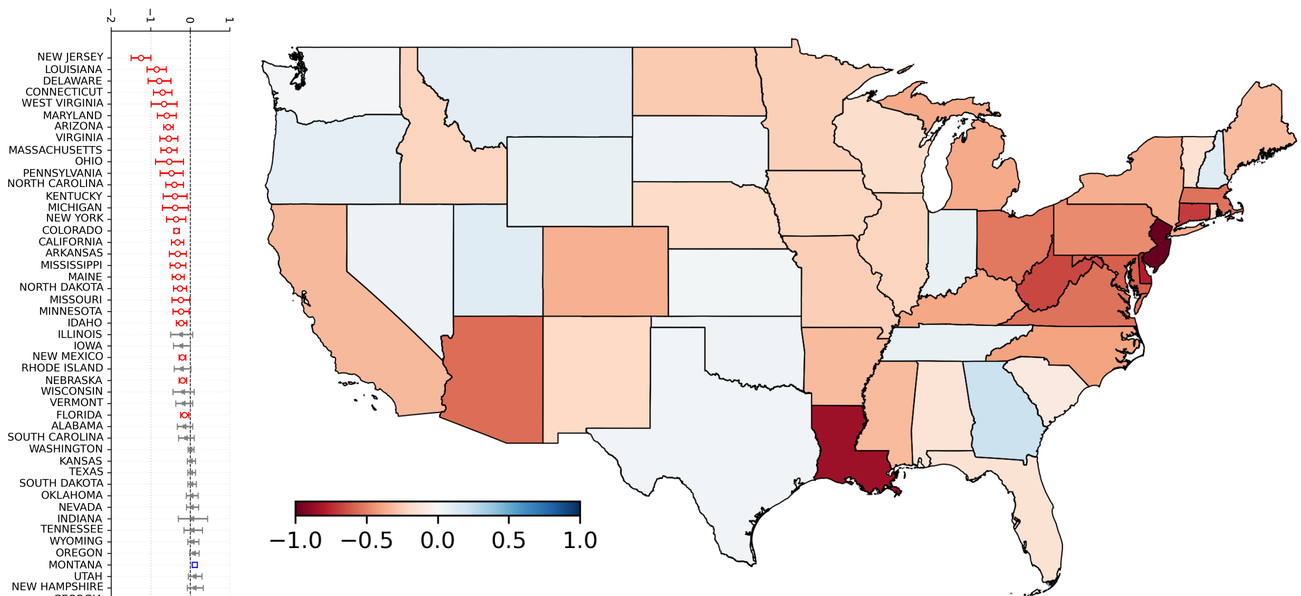


Figure 28. Impact of a shock in τ_t^k on economic activity, by industry