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

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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 sector-state dependent and networks expose sectors to weather shocks from other states through the use of intermediate inputs. I use annual data on sectoral GDP per capita and temperature anomalies by state from 1970 to 2019 to test 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 a fully transitory 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.

1 Introduction

In recent decades, the potential negative effects of climate change and global warming on the economy have motivated economists to develop models to understand and correctly measure the relevance of the interactions between the natural environment and economic performance. Extensive literature has shown that the effect of climate change is heterogeneous across countries and sectors and depends on geographical characteristics (Dell, Jones and Olken (2012), Colacito, Hoffmann and Phan (2018), and Hennessy, Lawrence and Mackey (2022)). Moreover, these effects do not only arise when the economy faces changes in long-term climatological conditions, often referred to as climate change, but also under short-run fluctuations, normally called weather (Dell, Jones and Olken (2014)). Indeed, the influence of such weather fluctuations is not bound by geographical limits due to the inherent linkages among economic agents. These connections are particularly strong for the United States, as shown by Barrot (2016) and Caliendo et al. (2018). Consequently, analyzing the role played by the heterogeneity and the interregional linkages naturally emerges to enhance understanding of the potential effects of weather anomalies and climate change on the economy.

In this paper, I study the macroeconomic implications on the aggregate economic activity of the United States, resulting from the heterogeneous sensitivity to weather anomalies[1] across states and sectors and the role played by the economic linkages when modeled as production networks. To measure the relevance of these channels, I built a multiregion-multisector model where sectors use production from other states as intermediate inputs. In this setting, weather fluctuations affect directly production through changes in productivity[2], but sectors are also exposed to fluctuations in other states through the consumption of intermediate inputs. I use data on sector production per capita at the state level and temperature anomalies from 1970 to 2019 to test the implications of this model. My re-

[1]Through the paper I use the terms weather fluctuations, weather deviations, and weather anomalies indifferently.

[2]In a meta-analysis, Hancock, Ross and Szalma (2007) shows a reduction in task performance when people are subject to thermal stressors. This suggests a close relationship between weather and labor productivity, which is equivalent to the productivity shifter in my model.

sults show that a model that does not include any of these characteristics underestimates the aggregate effect of weather fluctuations by at least two-thirds and that the additional effects caused by including any of these channels are similar in size[3]. In particular, I show that a sudden increase in temperatures of 1 Celsius degree decreases real gross production by 1.14 percent when both mechanisms are considered. Moreover, this impact depends on the size of the anomaly, with larger shocks causing more damage, demonstrating the crucial role played by the nonlinearities as in previous literature (Colacito, Hoffmann and Phan (2018),Deryugina and Hsiang (2014)). Furthermore, estimations reveal the differences in the sensitivity to weather fluctuations across states are due to regional-specific conditions rather than differences in sectoral composition. Additionally, they suggest that the exposure to weather anomalies in other states is as relevant as the direct effect caused by changes in own temperatures, showing the vital role played by the economic linkages. Finally, a sensitivity analysis suggests that my results are robust to different choices of temperature indicators and model specifications.

I start my analysis by presenting a simplified version of my baseline economy where the network connections are muted. Then, sector-state production is only exposed to weather shocks through the direct effect of temperature on productivity. It allows me to quantify the impact of weather shocks solely driven by the heterogeneity across sectors and states. In the empirical implementation of the model, I use annual information for 59 sectors and 48 states from 1970 to 2019 about economic activity and weather fluctuations. The former is measured as the real GDP per capita growth rate, while the latter is approximated by anomalies in average temperature. Given that I focus on a short-run analysis, I depart from the common use of temperature levels. Instead, I use the average deviations in monthly temperature with respect to their average in the last decade. This allows me to circumvent concerns regarding endogeneity and any anticipation mechanism that could bias my estimates. Following the literature (Burke, Hsiang and Miguel (2015)), I assume a nonlinear relationship between temperature and productivity.

[3]A similar conclusion is found by Rudik et al. (2022). However, their outcome variable is welfare.

My results confirm a nonlinear and heterogeneous impact of weather fluctuations across states and sectors. For example, at the state level, an unanticipated increase in temperatures by 0.5 standard deviations, or equivalently 0.3 Celsius degree, leads to significant negative responses in 11 states, while a temperature shock of 1.5 standard deviations, approximately 1 Celsius degree, contracts economic activity in 17 states. In both scenarios, Louisiana and New Jersey would be the states more affected by those shocks. At the industry level, a small temperature fluctuation would have a dispair effect, while sectors like agriculture, utilities, and real estate are negatively affected. In contrast, healthcare, management, and finance exhibit positive responses, possibly related to a higher appetite for investment during "sunny" days. This picture changes when the economy faces a large shock when no sector reports positive responses. 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.

As shown by Acemoglu, Johnson and Robinson (2002), climatological conditions can shape the set of economic activities developed in a specific geography, leading to differences in their economic structures. This can be especially true for a large country such as the United States, where different climate patterns coincide. Although this does not cause any identification problem in my estimation given my short-run strategy, some fraction of the average effect at the state level could be driven by differences in economic structure, understood as the sectoral composition of each state. To shed light on this possibility, I decompose the total effect of temperature into three components: (i) an economy-wide component, which shows the common effect in the whole economy; (ii) a structure-driven component that measures the fraction of the effect that is explained by discrepancies between the economic structure of a particular state and the average structure of the whole economy, and (ii) a regional-based component that accounts for particularities proper of each state. This analysis shows that -on average- 60 percent of the state-level response is explained by state-specific conditions, while only 16 percent of the differences are related to sectoral composition.

I measured the role played by the economic linkages by comparing the previous results with my main model where linkages are introduced in the form of production networks. In this economy, the final goods produced in a specific state can be used as intermediate output for the sectors located in any state. The production function is assumed to be Coob-Douglas[4] and exhibit constant returns to scale. By choosing this functional form, I obtain a well-defined solution that can be tested into actual data. The introduction of production networks generates two contrary effects regarding the aggregate effect of weather anomalies on the economy. On the one hand, since firms can substitute inputs from different regions, they can accommodate their demand to regions less affected by temperature, dampening the total effect of weather fluctuations. On the other hand, since the production in each state now depends on the productivity of their suppliers, firms are exposed to weather fluctuations in the other regions, amplifying the impact of weather shocks. To calibrate the parameters related to the Input-Output structure, I use data from the Commodity Flow Survey and the aggregate USE table.

My estimates show that accounting by production networks increases the negative effects of an unanticipated weather shock common to all states, with nonlinearities still playing a crucial role. At the geographical level, I find that the number of states with negative responses almost doubles when the economy faces a large weather shock, passing from 17 to 32. In the case of a small shock, this increment is lower, having now 13 states with a decline in economic activity. This is corroborated at the sector level, where 14 out of 20 sectors present a reduction in their economic activity when facing a large shock. Moreover, the positive effects on healthcare, management, and finance during small shocks disappear. Indeed, an inspection of the sector-state responses shows a shift to the left of the distribution for the small and the large weather shock with a fat tail compared with the distribution in the simplified model. This discrepancy is large as the size of the shock

[4]The results still hold up to first order when a CES function is used either in the utility function or in the production function

increases. Finally, a decomposition of the total effect of weather fluctuations by state reveals that -on average- the contribution of the own-state weather shocks (44 percent) is comparable to the portion explained by the exposure to other states weather conditions (56 percent).

At the macroeconomic level, including networks and heterogenous responses increase the exposure of the economy to weather fluctuations, with both channels being important. To show that, I estimate a simplified version of the model where both, heterogeneity and network effects are muted. This model suggests that an unexpected increase in temperature of 1 Celsius degree contracts the economy by -0.13 percent. Once heterogeneity is considered, this impact increases to -0.37, but at the expense of an increase in the variance of the estimates. In a second exercise, I include the network component into the model while heterogeneity is muted and estimate that the impact of a weather shock of a similar size would reduce the aggregate economic activity by -0.56 percent. In contrast, the estimates of my main model suggest that when both channels are activated, the reduction in economic activity is close to -1.14 percent. These results are similar to Dell, Jones and Olken (2012), Deryugina and Hsiang (2014), and Hsiang et al. (2017), although they focus on the long-run effect of climate change. It opens the discussion of whether the larger fraction of the effect of climate change is a long-run or a short-run phenomenon. A sensitivity analysis shows that these conclusions are robust to the variable used to measure temperature (average, minimum, or maximum), the choice of a reference point (10-year window, 20-year window, or 30-year window), and other specifications.

The structure of the rest of the paper is as follows. Section 2 shows a brief literature review. Section 3 introduces the simplified version of the theoretical model and show its results. Section 4 presents the main model and its implications at the sectoral and state level. Section 5 presents the macroeconomic implications of both models. Finally, section 6 concludes.

2 Related Literature

Two main strands of the literature nourish this paper. The first one uses econometrics models exploiting either geographical or sectoral variation to identify the economic impact of climate change and weather fluctuations in the United States. Before proceeding, it is important to note the difference between these two terms: while climate change refers to the changes in the long-term climatological patterns, weather denotes the short-run realization of such patterns. To fix ideas, we can imagine weather as the realization of temperatures, precipitation, wind, and other variables in a specific geography over some months or one year, while climate would be the average distribution of such patterns over decades[5]. As it is discussed by Dell, Jones and Olken (2014), the change in the time horizon simplifies identification in models that use weather as a covariate since exogeneity is not a strong assumption but limits the horizon in which their conclusions are valid. In fact, Dell, Jones and Olken (2012) using country annual data from 1950 to 2003 shows that temperature fluctuations have negatively affected the average growth rate of "poor countries" by 1.3 percent per Celsius degree while having an almost null effect in "rich countries" due to possible better adaptation mechanisms. This was in line with the initial macro-estimations that did not find a statistically significant effect of temperatures on the United States' economic activity. This adaptation mechanism was debated by Burke, Hsiang and Miguel (2015), who, using daily temperatures, county-level data, and a nonlinear panel model, finds that productivity, measured as income per capita, reduces by 1.7% per Celsius degree. Moreover, these estimates are not homogeneous across sectors and regions. Related to the former, Acevedo et al. (2020) shows 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. Regarding the latter, Hsiang et al. (2017) using multiple models shows that there is a high variability in estimated effects of climate change on the United States economic activity across geographies with clear differences between the

[5]For a more formal definition of climate can be found in Hsiang (2016)

north and south regions of the country. From these estimates, including nonlinearities and heterogeneity, look to play an important role in correctly estimating the impact of temperature fluctuations on economic activity. In this regard, this paper is -to the best of my knowledge- the first to exploit both of these features jointly to show their effect on real production. In fact, I show that an estimation that does not include sector and geographic heterogeneity would underestimate the effect of temperature anomalies.

The second strand comprises the papers that use general equilibrium models to either quantify the impact of climate change and weather variability on economic activity or to investigate some particular transmission mechanism in the United States. For example, Donadelli et al. (2017) builds a representative-agent model with recursive preferences and investment adjustment costs to find 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 closely related to the models that incorporate interconnections among sectors and regions in the form of production networks. A brief introduction and discussion on how the input-output linkages propagate micro shocks through the economy can be found Acemoglu et al. (2012) and Carvalho (2007). These connections are especially strong in the United States, as shown by Barrot (2016) and Caliendo et al. (2018). In the context of climate change, recently, Rudik et al. (2022) developed a dynamic spatial equilibrium model with input-output linkages, amenities, labor mobility, and other inefficiencies that help them overcome possible biases due to anticipation and adaptation. They find that climate change would reduce welfare in the United States, with states located in the South being negatively affected while those in the North would experience positive effects. Interestingly, the contributions to the total effect of climate change on the consumer welfare of the heterogeneous productivity and the input-output linkages are similar (-0.9pp for each one). Although my model and estimation are simpler, they can deliver a similar conclusion, with both mechanisms amplifying the impact of weather anomalies in a similar magnitude. Moreover, contrary to these documents, my paper focuses on the short-run effects, and, given the construction of my proxy for weather anomalies, it does not need to account for anticipation or adaptation to identify those short-run impacts correctly.

However, there are some caveats in my estimation. Firstly, the no inclusion of 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

I start by introducing a static model where the economy is composed of N geographies, each of them populated by J sectors that produce intermediate goods and one firm that produces the final good of the geography. All of them operate under perfect competition. I denote a particular geography and its final good by $n \in \{1, \ldots, N\}$ and a particular intermediate sector as $j \in \{1, \ldots, J\}$. The only factor of production is labor L, which is provided by a representative household that can freely move it across geographies[6]. For simplicity, assume that the representative household only receives utility from consuming final goods n and does not receive any disutility from providing its fixed labor stock. This

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

representative consumer has the following Cobb-Douglas preferences:

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

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

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 $\{\beta_n\}_i^N$:

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

with $P = \left(\prod_n \beta_n^{\beta_n}\right)^{-1} \prod_n (p_n)^{\beta_n}$ 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 geography n in the aggregate nominal GDP (PY).

In each geography, the production of intermediate goods y_n^j uses labor l_n^j as unique input but is exposed to a stochastic productivity shifter z_n^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 technology. 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 $\sum_j b_n^j = 1 \, \forall \, n$. In line with the extensive literature (see for example, textcolorred-mention some papers here), I assume that the productivity shifter $z_n^j(\tilde{\tau}_n)$ is driven partially by fluctuations in weather conditions of the geography 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 geography n. Moreover, the price index of the geography 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 assume a nonlinear relationship between productivity and weather conditions that I incorporate by defining the right-hand side of 6 as a quadratic function on $\tilde{\tau}$:

$$f(\tilde{\tau}_n) = \theta^j_{n1}\tilde{\tau}_n + \theta^j_{n2}(\tilde{\tau}_n)^2$$

each of the parameters $\theta^j_{n\ell}$ with $\ell = \{1,2\}$ can be expressed as $\theta^j_{n\ell} = \theta_{n\ell} + \theta_{j\ell} + \tilde{\theta}_{nj,\ell}$ where the sum of a geographical component θ_n, sector component θ^j and a sector-geography-specific deviation $\tilde{\theta}_{nj,\ell}$. Assuming that the expected value of this deviation is zero for all geographies and sectors entails the following theoretical regression:

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

Finally, combining equations 1 and 4 with the market clearing conditions imply that, in equilibrium, we can use the shares $\{\beta_n\}^N_n$ and $\{b^j_n\}^{N,J}_{n,j}$ as weighs to aggregate fluctuations in y^j_n:

$$d\ln Y = \sum_{n,j} \beta_n b^j_n d\ln y^j_n \tag{8}$$

3.1 Empirical implementation

In this subsection, I test whether actual data supports that short-run fluctuations in weather impact heterogeneously across geographies 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 geography 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. Something worth mentioning is that 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 that considers 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 in general] exacerbates the endogeneity problems caused by the anticipation and adaptation of economic agents. To address these sources of inconsistency, I focus my analysis on short-run movements that can be easily assumed as unanticipated and exogeneous from human activity. To do so, I use the following formula:

$$\tilde{\tau}_{nt} = \frac{1}{12}\sum_{m} \tilde{\tau}_{nmt} \quad \text{with} \quad \tilde{\tau}_{nmt} = \tau_{nmt} - \bar{\tau}_{nmt} \tag{9}$$

where τ_{nmt} represents the average temperature for the state n during the month m in year t, and $\bar{\tau}_{nmt}$ is the average temperature for the same month m over the past 10 years. In this way, $\tilde{\tau}_{nmt}$ captures temperature fluctuations relative to a local trend. While climatological literature often uses a 30-year basis as temperature normals, 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[7]. Then, I run the following regression:

$$\Delta\tilde{y}_{j,n,t} = \alpha + \rho_j \Delta\tilde{y}_{j,n,t-1} + \left(\delta_{1n} + \gamma_{1j}\right)\tilde{\tau}_{n,t} + \left(\delta_{2n} + \gamma_{2j}\right)\tilde{\tau}^2_{n,t} + \theta_j + \theta_t + \theta_n + \epsilon_{j,n,t} \tag{10}$$

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 (θ_j), state fixed effects (θ_n), and time fixed effects (θ_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)).

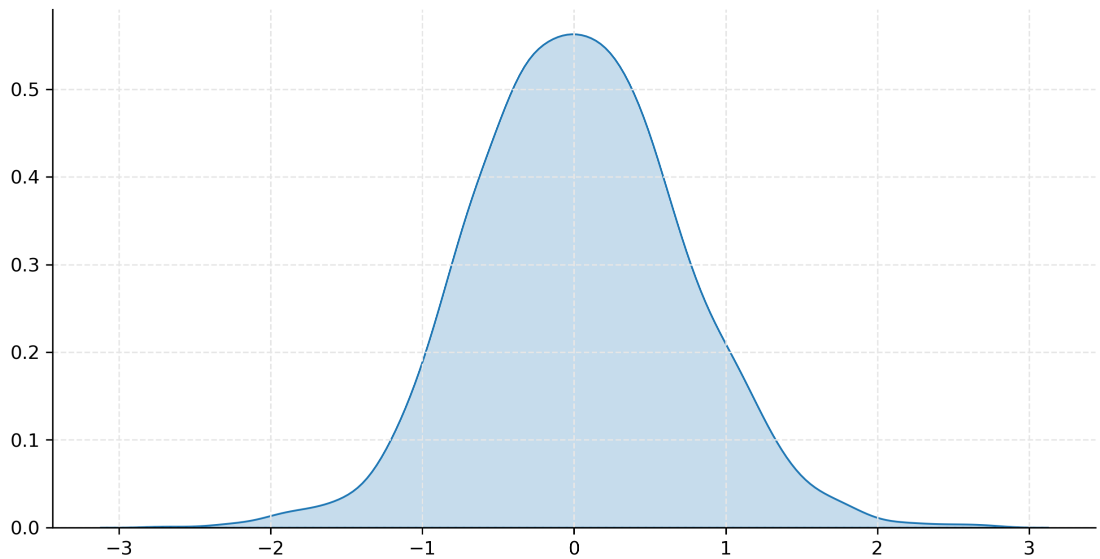
Equation 10 accommodates nonlinear effects by including the square of the weather shock ($\tilde{\tau}^2_{nt}$). It permits a different impact between small and large shocks. It is motivated by the understanding that small changes in temperature could lead to either beneficial or adverse effects, while 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

[7] 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 facilitate exposition, I refer $\tilde{\tau}^{\text{adjusted}}_{nt}$ simply as $\tilde{\tau}_{nt}$ for the remainder of the paper

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 short-run temperature fluctuations $\tilde{\tau}$: 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 δ_{2n} and γ_{2j}, 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 $\tilde{\tau}^0$ to 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[8]. $\mathcal{G}_{jn}$ is standardized per Celsius degree to improve comparability.

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

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[9] 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.

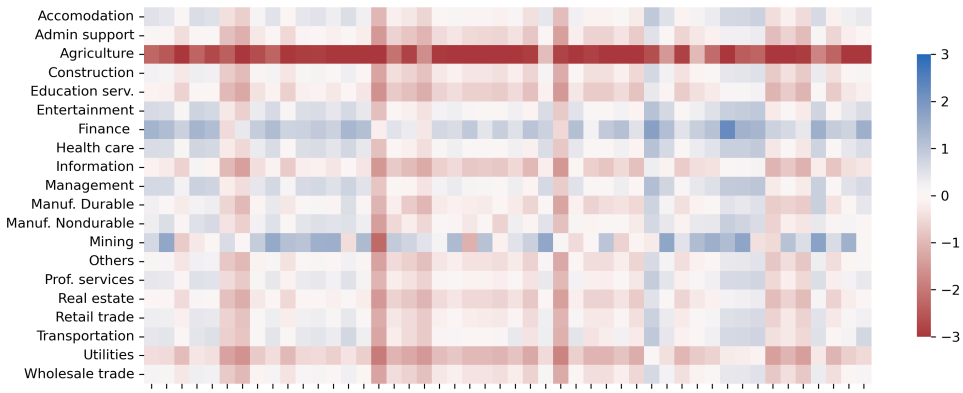
The results from both panels underscore the presence of heterogeneities across sectors and states, alongside the differences that emerge between small and large weather fluctuations due to the nonlinear dynamics embodied in the regression. The effects of small shocks are characterized by mild and occasionally positive impacts, while large

[8]with a variance: $\sigma^2_{\hat{\delta}_1} + \sigma^2_{\hat{\gamma}_1} + (\tilde{\tau}^o)^2\left(\sigma^2_{\hat{\delta}_2} + \sigma^2_{\hat{\gamma}_2}\right) + 2\sigma_{\hat{\delta}_1,\hat{\gamma}_1} + 2\tilde{\tau}^o\left[\sigma_{\hat{\delta}_1,\hat{\delta}_2} + \sigma_{\hat{\delta}_1,\hat{\gamma}_2} + \sigma_{\hat{\gamma}_1,\hat{\delta}_2} + \sigma_{\hat{\gamma}_1,\hat{\gamma}_2}\right] + 2(\tilde{\tau}^o)^2\sigma_{\hat{\delta}_2,\hat{\gamma}_2}$

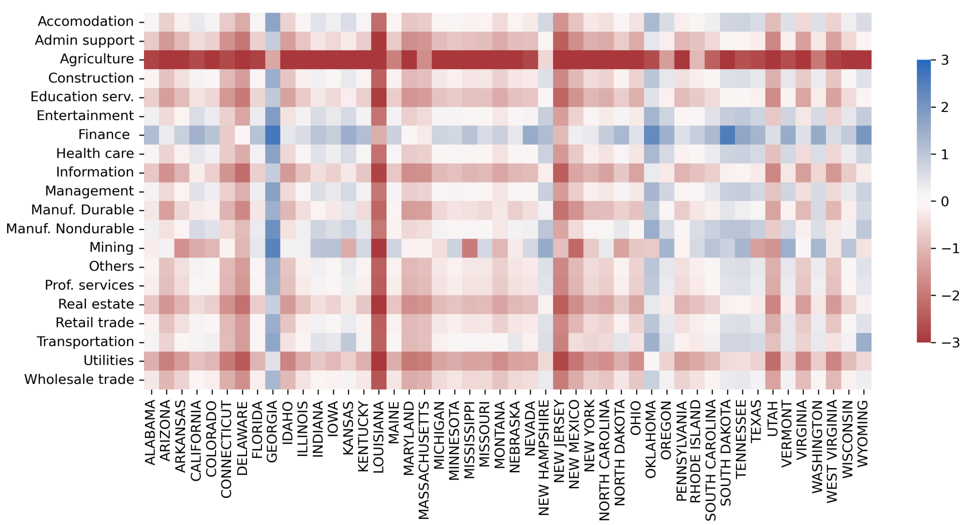
[9]As reported by the NOAA, the average increase in temperature per decade was around 0.27 Celsius degree since 1980.

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

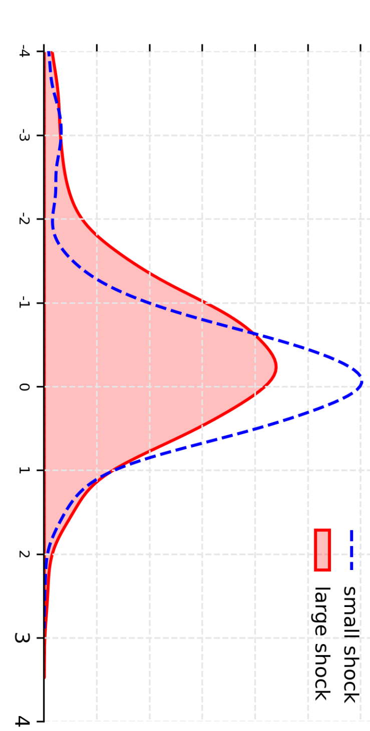
(a) Small shock: $\tilde{\tau}^o = 0.5\sigma_{\tilde{\tau}}$



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



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



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. Panel (c) plots a comparison in the distribution of $\mathcal{G}_{ln}$ under both sizes of shocks.

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 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 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 panel 2c, 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 $\mathcal{G}_j(\tilde{\tau}^o_{n,t})$.To compute each of these objects, I use the following equations:

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

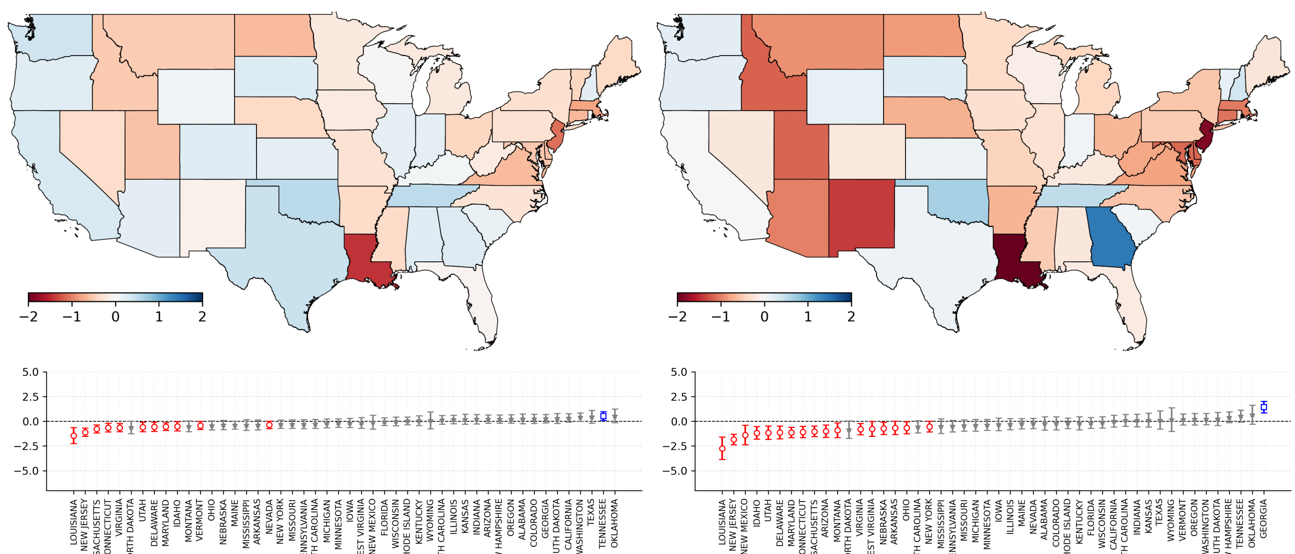
$$\mathcal{G}_l(\tilde{\tau}^o_{n,t}) = \textstyle\sum_g w^b_{ln}\mathcal{G}_{ln}(\tilde{\tau}^o_{n,t}), \qquad w^b_{ln} = \frac{1}{T}\sum_t \left(\frac{nGSP_{ln}}{\sum_g nGSP_{ln}}\right)_t \tag{13}$$

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 3a and 3b in Figure 3. 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.

Figure 3. Impact of weather fluctuations on economic activity at state level $\mathcal{G}_n$, per unit Celsius

(a) Small weather shock $\tilde{\tau}^0 = 0.2$ **(b)** Large weather shock $\tilde{\tau}^0 = 1.4$



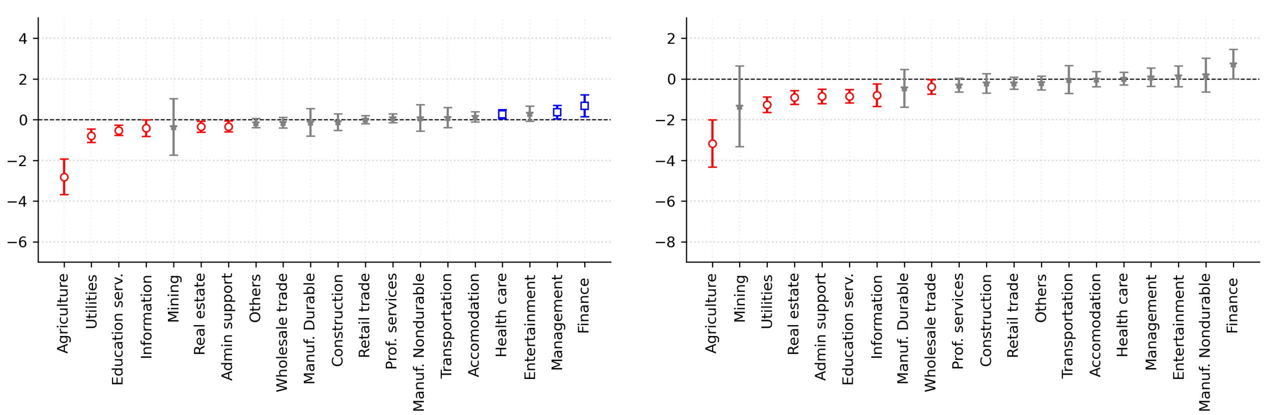
Note: Panels (a) and (b) showed the difference in the average growth rate per state with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the sector 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.

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 4 presents the distribution of G_l under the small and the large weather anomalies. In line with the extensive 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 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.

Figure 4. 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 $\tilde{\tau}^0 = 1.5\sigma_{\tilde{\tau}}$

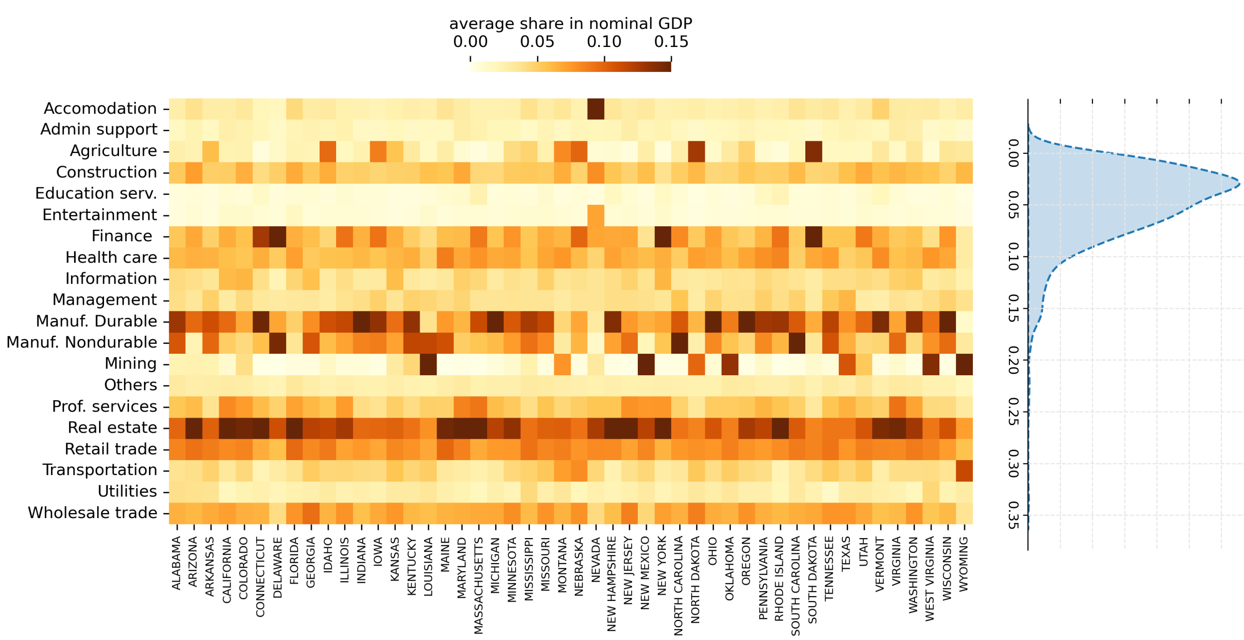


Note: Panels (a) and (b) showed the difference in the average growth rate per industry with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the state's 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.

- 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 5 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 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 require distinct developmental approaches to assess the risk involved.

Figure 5. 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.

Let $\bar{w}^a_j = \frac{1}{T}\sum_t \left(\frac{nGDP_{jt}}{nGDP_t}\right)_t$ 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:

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

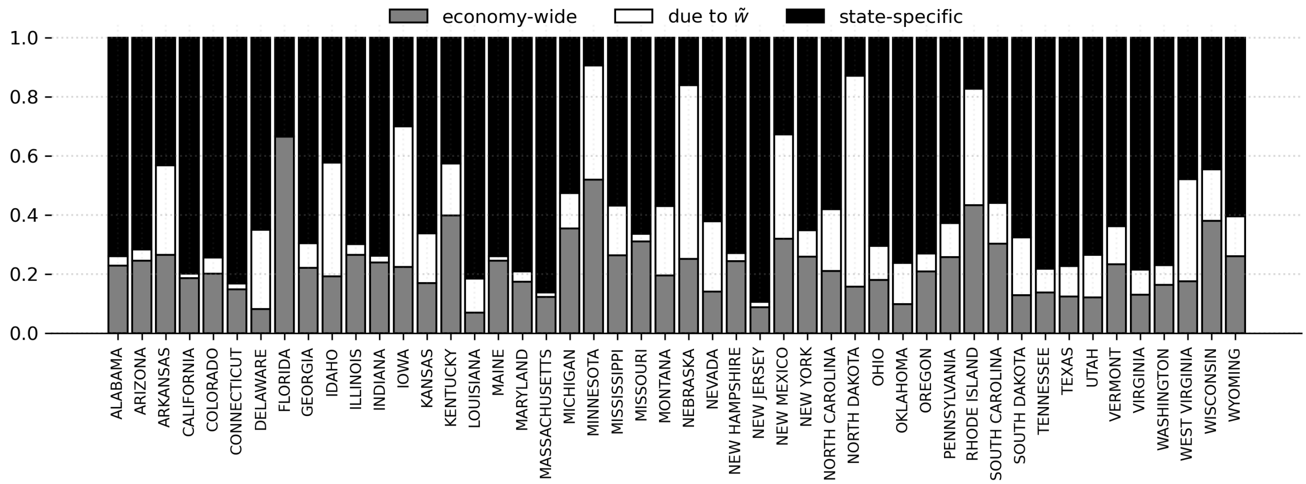
where variables with tilde $\tilde{w}^a_j = w^a_{jn} - \bar{w}^a_j$ and $\tilde{\mathcal{G}}_{jn} = \mathcal{G}_{jn} - \mathcal{G}_j$ are defined as the differences of the state-specific value of the variable with respect to its average. The first component of equation 14 represents the economy-wide effect, which I assume is unrelated to specific 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 6 plots the contribution of each of these components under the small (panel 6a) and the large weather anomaly (panel 6b). 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.

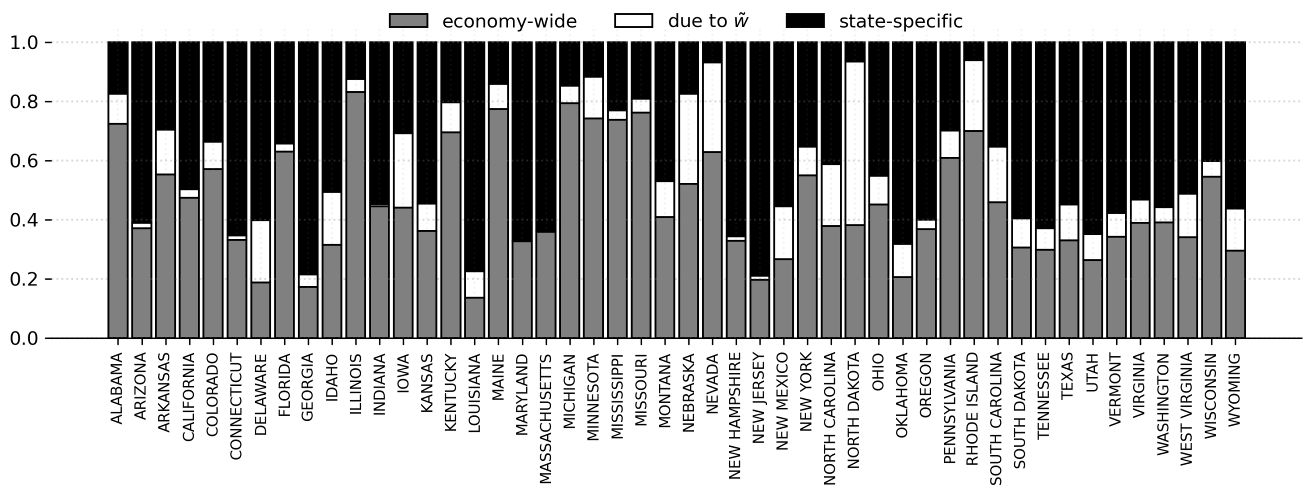
Results show that the largest fraction of the observed heterogeneity is explained by regional-specific conditions reflecting the importance of the geographical dimension and how economic activity is shaped by the environment. In the case of a small weather shock, the differences in economic structure are responsible for around 16 percent of the heterogeneity, while the regional-specific conditions account for nearly 60 percent. When

Figure 6. 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.

regions face a large weather anomaly, the contribution of these 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 denoted 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[10] and the observed growth rates. Mathematically, $\mathcal{H}_{jn}$ can be calculated with the formula:[11]

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

As before, we can aggregate the results of $\mathcal{H}_{sg}$ at the geographical and at the industry level as follows:

$$\begin{aligned} \mathcal{H}_n(\sigma^2_{\tilde{\tau}}) &= \textstyle\sum_s w^a_{jn}\mathcal{H}_{jn}(\sigma^2_{\tilde{\tau}}) \quad (16)\\ \mathcal{H}_l(\sigma^2_{\tilde{\tau}}) &= \textstyle\sum_g w^b_{ln}\mathcal{H}_{ln}(\sigma^2_{\tilde{\tau}}) \quad (17) \end{aligned}$$

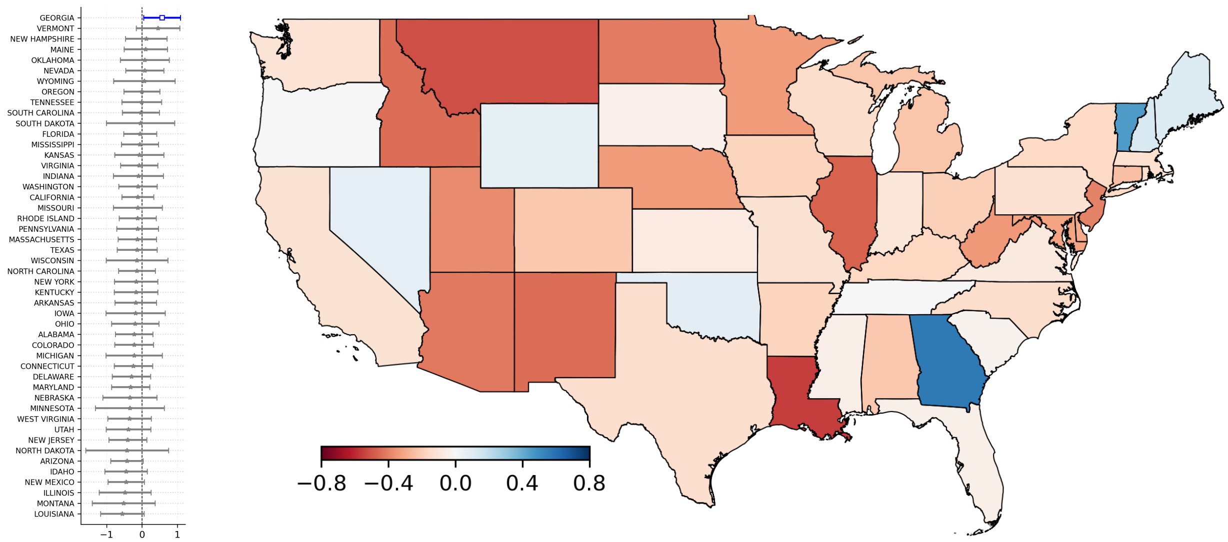
The distribution of $\mathcal{H}_n$ and its confidence interval for a probability range of 90 percent plotted in figure 7 support the short-run nature of my exercise. In average terms, we can see that most states would benefit from a scenario without short-run deviations

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

[11]From Seltman 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 $\mathcal{H}_{sg}$ and assuming $\sigma^2_{\tilde{\tau}}$ being constant, I have:

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

Figure 7. 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.

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 reveals that this expected effect is not statistically significant. This reveals that the approach to measuring $\tilde{\tau}$ successfully isolates only fluctuations in the short run.

4 The role of interregional linkages

4.1 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. The new production function for intermediate goods is:

$$y_n^j = z_n^j(\tilde{\tau}_n)\left(l_n^j\right)^{\tilde{\alpha}_n^j}\prod_m\left(x_{nm}^j\right)^{a_{nm}^j} \tag{18}$$

where the pair $x_{n,m}$ is the amount of final goods m that the sector y_n^j buys to use them as materials. The constant returns to scale assumption implies $\alpha_n + \sum_m a_{nm} = 1 \,\forall\, n$. The optimality conditions for the intermediate-good firms are:

$$a_{nm}^j = \frac{p_m x_{nm}^j}{p_n^j y_n^j} \tag{19}$$

$$\alpha_{nm}^j = \frac{w l_n^j}{p_n^j y_n^j} \tag{20}$$

let g_n^j denote the real value added (or real GDP) by the sector j located in the region n. Since $g_n^j = \frac{w l_n^j}{p_n^j}$, we can use equation31 express the fluctuation of the real GDP by sector-state as:

$$d\ln g_n^j = d\ln y_n^j$$

Replacing 30 and 31 into the production function of the intermediate goods and considering that the optimality condition of the final firm implies a price index equal to $P_n = \prod_j\left(p_m^j\right)^{b_m^j}$, we obtain:

$$\frac{p_n^j}{w} = \zeta * \left(z_n^j(\tilde{\tau}_n)\right)^{-1}\prod_{m,j}\left(\frac{p_m^j}{w}\right)^{b_m^j a_{nm}^j} \tag{21}$$

let $\hat{p}_n^j = \frac{p_n^j}{w}$ denote the real price of y_n^j. Then, after taking logs, differentiating both sides of equation 21, and expressing it as an array, we have the following expression:

$$\mathrm{d}\ln\hat{\boldsymbol{p}} = -\Psi\mathrm{d}\ln\mathbf{z}(\tilde{\boldsymbol{\tau}}) \quad \text{with } \Psi = (I - A) \tag{22}$$

where $\ln\hat{\boldsymbol{p}} = \left[\hat{p}_1^1, \hat{p}_1^2, ...\right]^T$ is a column vector composed of the relative prices of the state-specific intermediate goods. The matrix A collects all the coefficient $b_m^j a_{nm}^j$ 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 shock z_n^j has in all the other sectors y_m^i of the economy.

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 30, we obtain the following relation:

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

that can be introduced in the market clearing condition $y_n = c_n + \sum_m \sum_j x_{mn}^j$ to reach the following result:

$$\frac{y_n}{c_n} = 1 + \sum_m \left(\frac{\beta_m}{\beta_n} \sum_j a_{mn}^j b_m^j \right) \frac{y_m}{c_m} \tag{23}$$

Equation 33 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. Moreover, we can express the change in the real GDP of the geography n as a weighted sum of the fluctuations in GDP of their sectors using the share of the sector j in the nominal GDP of the region n as weigh as it is shown by equation 24

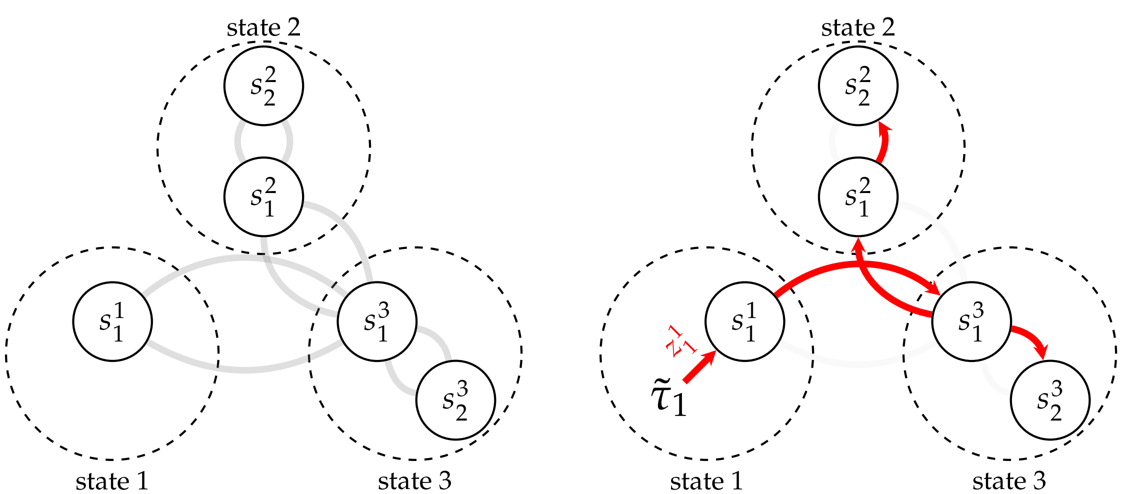
$$\mathrm{d}\ln y_n = \mathrm{d}\ln c_n = \sum_j b_n^j \mathrm{d}\ln y_n^j = \sum_j b_n^j \mathrm{d}\ln g_n^j \tag{24}$$

Finally, we can use 2 to show that $d\ln \hat{p}_n = d\ln c_n$, and then combine it with the expression for the price index of the geography n and the equation 24 to obtain:

$$\mathrm{d}\ln g_n^j = \underbrace{\mathrm{d}\ln z_n^j(\tau_n)}_{\text{own effect}} + \overbrace{\sum_{i,m} (\psi_{nm}^{ji} - \mathbf{1}_{n=m,j=i}) \mathrm{d}\ln z_m^i(\tau_m)}^{\text{network effect}} \tag{25}$$

The propagation of a weather shock through the economy can be understood using a simple example. Suppose an economy is composed of three states and two sectors, and one produces 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 8. To simplify the explanation, let s_i^l denote the production of the good i in the state l. As it is shown by 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 s_1^3 uses the production of s_1^1 as intermediate input, its production is directly affected in a first round. Given that s_1^3 is used as an intermediate input for s_1^2 and the nontradable good s_2^3, both production reduces in a second round. This pattern continues, creating a cascade of negative shocks. This simple example allows us to visualize the importance of controlling by these network effects to capture the actual impact of weather shocks on the whole economy.

Figure 8. Transmission of a state-specific weather shock



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

4.2 Empirical implementation

Equation 37 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 provided by 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 intermediates 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[12]. 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,

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

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 homogenous 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 $\tilde{b}^{l,m}_{,j} = \frac{b^{l,m}_{,j}}{\sum_h b^{l,h}_{,j}}$ 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 $\tilde{\tau}^{network}_{jnt}$ to 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 37 to be estimated is:

$$\Delta\tilde{y}_{j,n,t} = \alpha + \rho_j \Delta\tilde{y}_{j,n,t-1} + \left(\delta_{1n} + \gamma_{1j}\right)\tilde{\tau}_{n,t} + \left(\delta_{2n} + \gamma_{2j}\right)\tilde{\tau}^2_{n,t} + \zeta_{1n}\tilde{\tau}^{network}_{jnt} + \zeta_{2n}\left(\tilde{\tau}^{network}_{jnt}\right)^2 + \theta_j + \theta_n + \theta_t + \epsilon_{j,n,t} \tag{26}$$

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 due to 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 due to 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 need to 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:

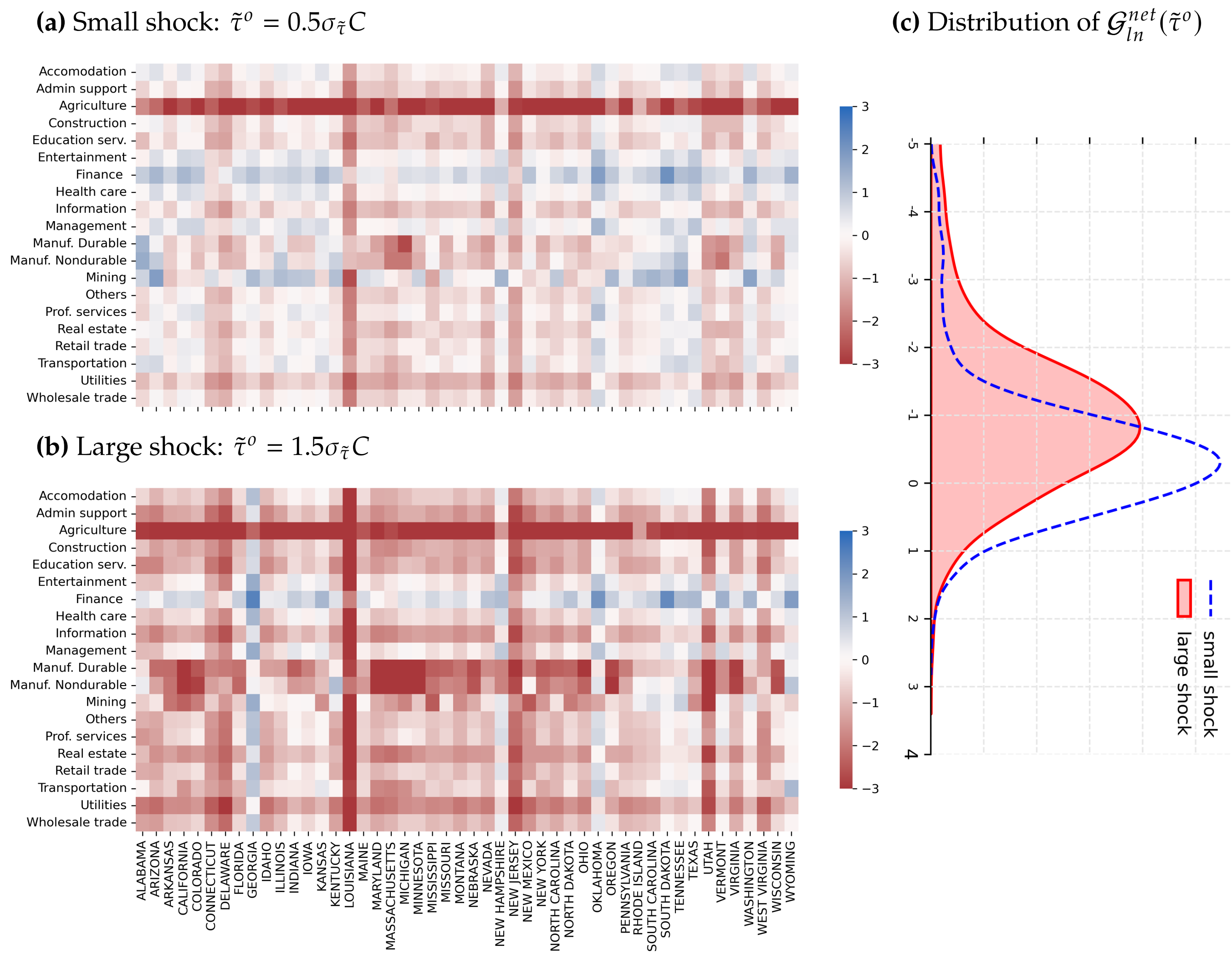
$$\mathcal{G}^{network}_{jn}(\tilde{\tau}^o) = (\hat{\delta}_{1n} + \hat{\gamma}_{1j}) + (\hat{\delta}_{2n} + \hat{\gamma}_{2j})\tilde{\tau}^o + \hat{\zeta}_{1n}\ell_{jn} + \hat{\zeta}_{2n}\ell^2_{jn}\tilde{\tau}^o \quad \ell_{jn} = \sum_{i,m}\left(\psi_{jn,im} - \mathbf{1}_{jn=im}\right) \tag{27}$$

Results depicted in Figure 9 show that the nonlinear effects of weather shocks become stronger once we account for interregional linkages. This figure plots the estimated impact of weather shocks on real production by sector-state using the same structure as the one reported in the previous section. After inspecting it, three main observations come to light. First, from panel 9c, it is evident that the distribution of $\mathcal{G}_{ln}^{net}$ under a large weather shock has a more negative average (-1.06 percent under a large shock versus -0.40 in the small shock case) and a larger variance (0.86 for the small shock and 1.6 for the large shock). This difference is larger compared to the case in which only heterogeneity was considered. Second, the contraction in economic activity is not concentrated in particular sectors or states, as noted from panels 9a and 9b, reflecting the economy-wide nature of the network linkages. Finally, the role of the networks as a transmission mechanism of weather fluctuations is not being activated only by the nonlinearities embodied in the estimation. It is clearer when we compare the distribution of $\mathcal{G}_{ln}$ for the same shock size with respect to the model with only heterogeneity reported in figure 10.

At a geographical level, 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 11, which presents the effect -per unit Celsius- of small and large weather fluctuations on economic activity at the state level. As before, the weights used to aggregate $\mathcal{G}_{ln}$ were the sector's share in the state's GDP. Similarly to the model with only heterogeneity, small weather fluctuations cause significant negative impacts only in one-quarter of the states (panel 11a). 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 strong for the states in the West and Middle-West regions of the United States, such as California, Oregon, and Michigan.

As depicted by Figure 12, accounting for sectoral interactions amplifies the negative effect of weather shocks on both tradable and nontradable sectors. This figure provides

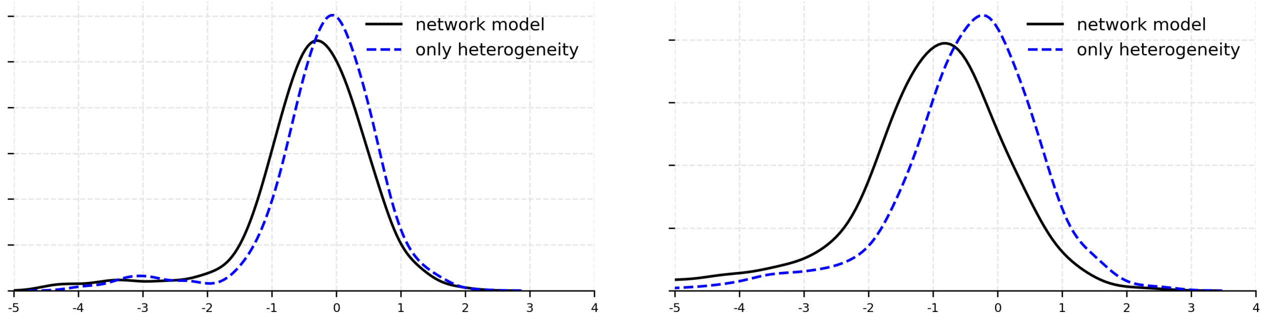
Figure 9. Impact of $\tilde{\tau}^o$ on economic activity, model with heterogeneities and networks



Note: Panels (a) and (b) show the difference in the growth rate with respect to a scenario with no weather shocks $\tilde{\tau} = 0$. 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 degrees Celsius, 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. Panel (c) plots a comparison in the distribution of $\mathcal{G}_{ln}$ under both sizes of shocks.

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 control for economic linkages. Second, when the economy faces a large weather shock the economic activity of two out of three contracts is displayed by panel 12b. In comparison with the model that only allows heterogeneous response, the number of negatively affected sectors by a large weather fluctuation increases from 7 to 14. In particular, both type of manufacturing (durable and nondurable) reports a statistically significant contraction of around

Figure 10. Distribution of $\mathcal{G}_{ln}$, comparison of models

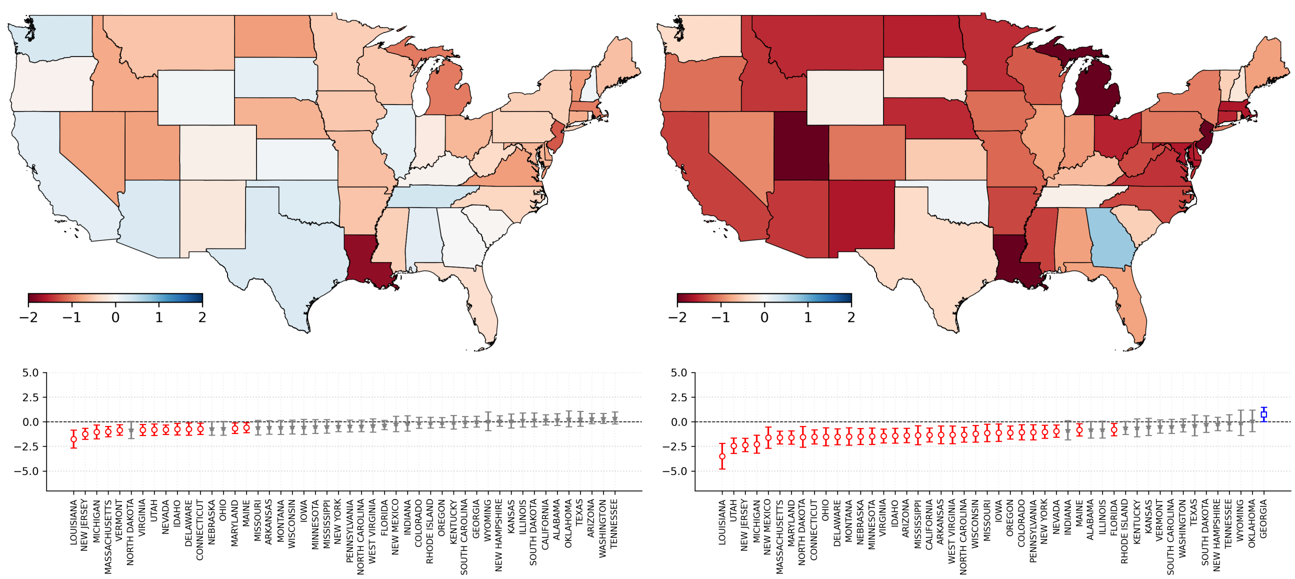


(a) small $\tilde{\tau}$ shock **(b)** large $\tilde{\tau}$ shock

Note: Kernels show the distribution of the impact of a weather shock on industry-state economic activity. Each panel compares the responses between the model with only heterogeneities from the previous sections and the model with heterogeneities and network effects. Panel (a) displays the comparison when the economy is hit by a small weather shock. Panel (b) depicts the comparison when the economy faces a large weather shock.

Figure 11. 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 $\tilde{\tau}^0 = 1.5\sigma_{\tilde{\tau}}$

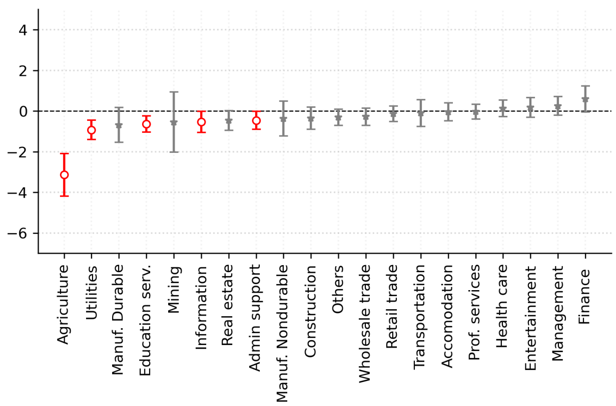


Note: Panels (a) and (b) showed the difference in the average growth rate per state with respect to a scenario with no weather shock $\tilde{\tau} = 0$. Changes are reported per unit Celsius to allow comparison between the two shocks. The average growth rate was computed as a weighted sum of the sector 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.

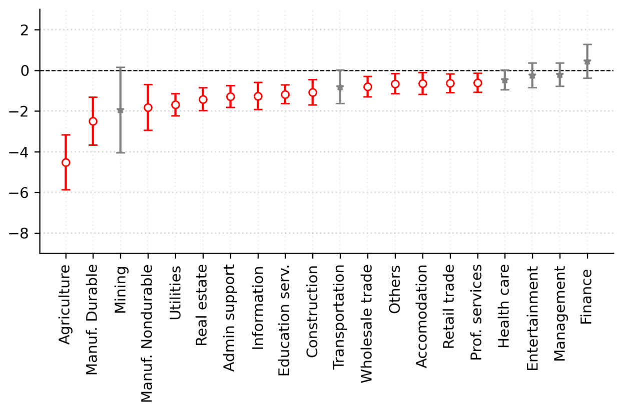
-2.5 percent and -1.8 percent, respectively. Third, although the transmission mechanism of state-specific weather shock relies on interregional trade, its effects are also visualized in nontradable sectors. This is particularly the case for Construction and Accommodations that pass from not showing significant responses to reporting statistically significant negative responses.

Figure 12. Impact of weather fluctuations 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.

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

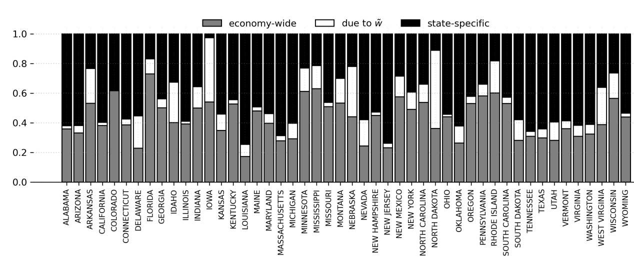
In a model with interregional linkages, there are two relevant dimensions in which the heterogeneity in $\mathcal{G}_{jn}^{network}$ can be decomposed. The first dimension explains the economic source of these differences by isolating the fraction of the impact explained by differences in the economic 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 37, we called as direct and network effect, respectively. Both decompositions are shown in Figure 13.

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 13 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 during normal times.

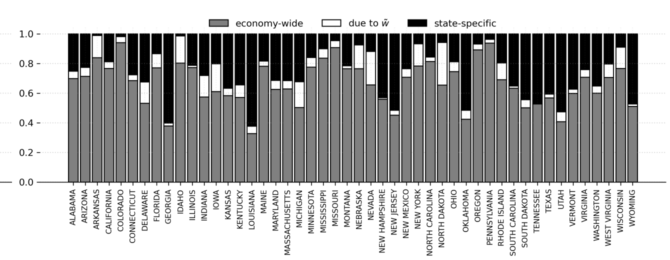
In terms of geographical source, both the direct and network effects explain a good portion of the total impact of weather fluctuations on the economy as depicted by panels (c) and (d) of Figure 13. On average, during normal times, the contribution of the network effect is around 56 percent. This component is particularly important for the states of Indiana and Tennessee, where it explains more than 85 percent of the total impact of weather anomalies. Conversely, when the economy faces a large weather shock, the average contribution of the network component reduces to 47 percent, suggesting a relatively stable ratio between these two components.

Figure 13. Decomposition of $\mathcal{G}_n$

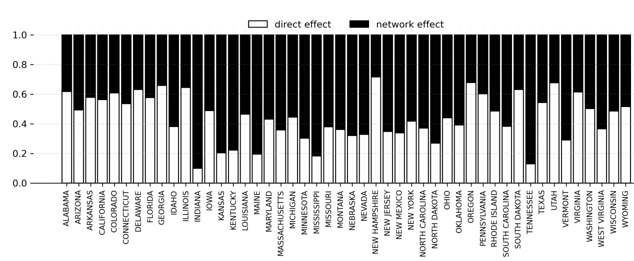
(a) Small weather shock



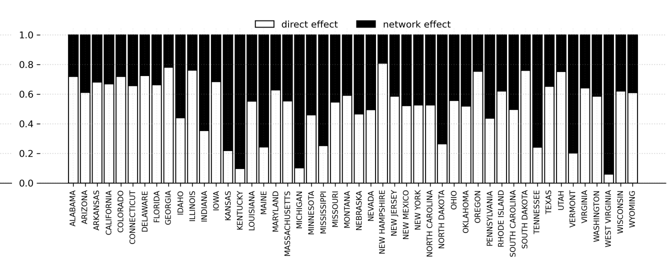
(b) Large weather shock



(c) Small weather shock



(d) Large weather shock



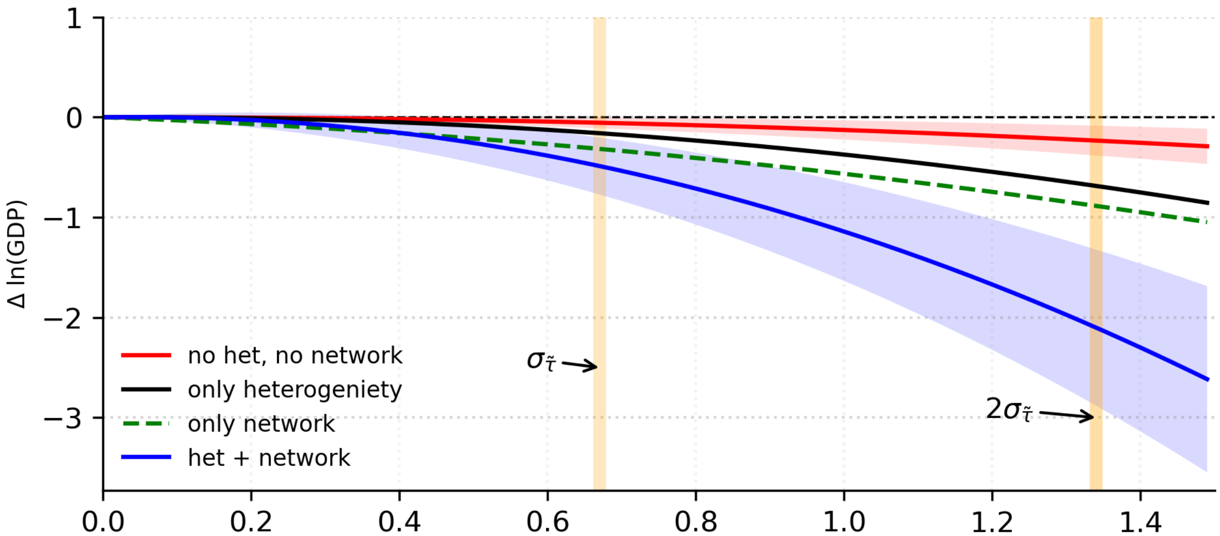
Note:

5 Macroeconomic implications of heterogeneity and network linkages

In the previous sections, I demonstrated that there is high variability in the impact of weather anomalies on economic growth across sectors and states and that these effects are amplified when we control for economic linkages in the form of production networks due to the propagation mechanism that the model offers. *What are the implications of these two observations to the economy as a whole?* In this section, I show that the presence of such heterogeneities and network effects predict a larger impact of weather fluctuations on the economy. This difference is clearer as the shock becomes larger due to the underestimated nonlinear effect that an aggregate regression obtained.

The inclusion of heterogeneity in the model, amplifies the total effect of temperature anomalies by making more relevant the nonlinear effects. I start the macroeconomic analysis by estimating an econometric model that does not consider heterogeneity or linkages. To maintain consistency with section 3, I estimate the specification 10 under the assumption that the effect across sectors and states is invariant and equal to φ_1 for the linear effect, and φ_2 for the quadratic effect. Additionally, the coefficient associated with the lag was restricted to be invariant across sectors. Results from this model, which are reported in the first column of the table 1, show a negative effect of larger weather shocks reflected in the sign and statistical significance of the coefficient $\hat{\varphi}_2$. For example, an increase in unexpected temperature by 0.3 Celsius degrees reduces -per unit Celsius- the aggregate economic growth by around -0.03 percent, while an increase in temperature of 1 Celsius degree causes a contemporaneous reduction of -0.13 percent. These impacts are higher in the model presented in section 3, where an increase in temperatures of 0.3 Celsius degrees reduces -per unit Celsius- the economic growth by -0.09 percent. In contrast, an unexpected increase in temperatures of 1 Celsius degree, would reduce the economic activity by -0.37 percent. These differences are more notorious in Figure 14, where I plot the total impact on the aggregate economic performance of a generalized increase in temperature deviations $\tilde{\tau}$ for different models. In this figure, the red line displays the total effect on economic growth estimated by a model with no heterogeneity or networks, while the black line refers to the model in section 3. To show whether these differences are due to a linear or quadratic effect, I perform a "back to the envelope" calculation. In this exercise, I regress $\tilde{\tau}$ and $\tilde{\tau}^2$ on the total effect $\mathcal{G}(\tilde{\tau})$ obtained from the model in section 3 at 150 different levels of $\tilde{\tau}$ evenly distributed in the interval $\tilde{\tau} \in [0, 1.5]$. The results of this exercise suggest a downward bias of the nonlinear effect when heterogeneity is not allowed, as reported in the third column of table 1.

Figure 14. Short-run 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 dashed green line depicts the impact estimated by a model that includes networks but assumes a homogeneous response across sectors and states. 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 $\tilde{\tau}$

Controlling for network linkages across states increases the macroeconomic effect of increases in temperature. To show that the inclusion of networks is important by itself and they do not require interaction with heterogeneity to have significant implications, I estimate a model similar to the specification in section 4 but assuming that the responses across sectors and states are homogeneous as follows:

$$\Delta\tilde{y}_{j,n,t} = \alpha + \rho\Delta\tilde{y}_{j,n,t-1} + \delta_1\tilde{\tau}_{n,t} + \delta_2\tilde{\tau}^2_{n,t} + \zeta_1\tilde{\tau}^{netw}_{jnt} + \zeta_2\left(\tilde{\tau}^{netw}_{jnt}\right)^2 + \theta_j + \theta_n + \theta_t + \epsilon_{s,g,t} \quad (28)$$

the aggregate effect $\mathcal{G}$ is plotted as a dashed green line in Figure 14, while the estimated coefficients are reported in the last row of the table, and the implicit linear and quadratic effects from the "back to the envelope" calculation in column (2) of the same table. To obtain the left-hand side variable $\mathcal{G}$ required to estimate the implicit $(\hat{\varphi}_1, \hat{\varphi}_2)$, I compute the impact of an increase in $\tilde{\tau}$ conditional on the average value of the components of $\tilde{\tau}^{netw}_{sgt}$ associated only to the calibrated Leontief-inverse matrix described by ℓ_{sg} in equation 27. From Figure 14 we can observe a more negative macroeconomic impact of temperature deviations at any shock size. This is reflected as a shift to the left in both implicit coefficients. Comparing the raw estimates of $(\hat{\delta}_1, \hat{\delta}_2)$ with $(\hat{\zeta}_1, \hat{\zeta}_2)$ reveals that these results are driven by the role of the network rather than changes in the direct effect of temperatures deviations. A simple comparison against the model in section 3 suggest that the propagation caused by the inclusion of the network is larger that the amplification resulting from the heterogeneities. Indeed, from the perspective of the two shock size that I use during the whole paper, we can see that an unanticipated increase in temperatures of 0.3 Celsius degree reduces the contemporaneous growth rate by around -0.37 percent while the effect of a one-Celsius degree shock is about -0.56 percent, both results are larger than their counterparts with only heterogeneity.

Table 1. Linear and quadratic coefficients, regression $\tilde{\tau}$ on $\mathcal{G}$

	No Heterogeneity		**Heterogeneity**	
	Not network	Network	Not network	Network
$\hat{\varphi}_1$	0.01 (0.87)	-0.27	0.04	0.14
$\hat{\varphi}_2$	-0.14 (0.02)	-0.28	-0.40	-1.25

$\hat{\delta}_1 = 0.20\,(0.02)$ $\quad \hat{\delta}_2 = -0.07\,(0.30)$

$\hat{\zeta}_1 = -0.50\,(0.00)$ $\quad \hat{\zeta}_2 = -0.23\,(0.03)$

p-values in parenthesis

Note: The estimated model in columns 2-4 is $\mathcal{G}(\tilde{\tau}) = c + \varphi_1^{(i)}\tilde{\tau} + \varphi_2^{(}i)\tilde{\tau}^2 + \epsilon$. The considered models were: (a) model with networks in column 2, (b) model with heterogeneities in column 3, and (c) model with heterogeneity and networks in column 4. Coefficients $\hat{\varphi}_1$ and $\hat{\varphi}_2$ reported in the first column were obtained from a linear regression of $\tilde{\tau}$ on $\Delta\tilde{y}_{sgt}$ controlling by sector, time, and state FE and one lag of economic activity.

The interaction between heterogeneities and networks increases the nonlinear effect of temperature on the economy by more than the simple addition of both channels. This is visible in Figure 14 where the effect of temperature deviations estimated from the model in section 4 is depicted with a solid blue line. As the shock increases, the distance between the results of this model accentuates. In particular, for an increase of 1 Celsius degree, this model estimates an aggregate impact of around -1.14 percent. This is larger than the sum of the effect of the models previously presented. Surprisingly, this model estimated a smaller impact of temperatures for small shocks. In particular, the model predicts that an increase of 0.3 Celsius degree reduces real production by -0.26 percent, which is larger than the model that includes only heterogeneities but smaller than the model that includes only networks. The implicit coefficients $(\hat{\varphi}_1, \hat{\varphi}_2)$ suggest that this is due to an increase in the relative importance of the nonlinearities.

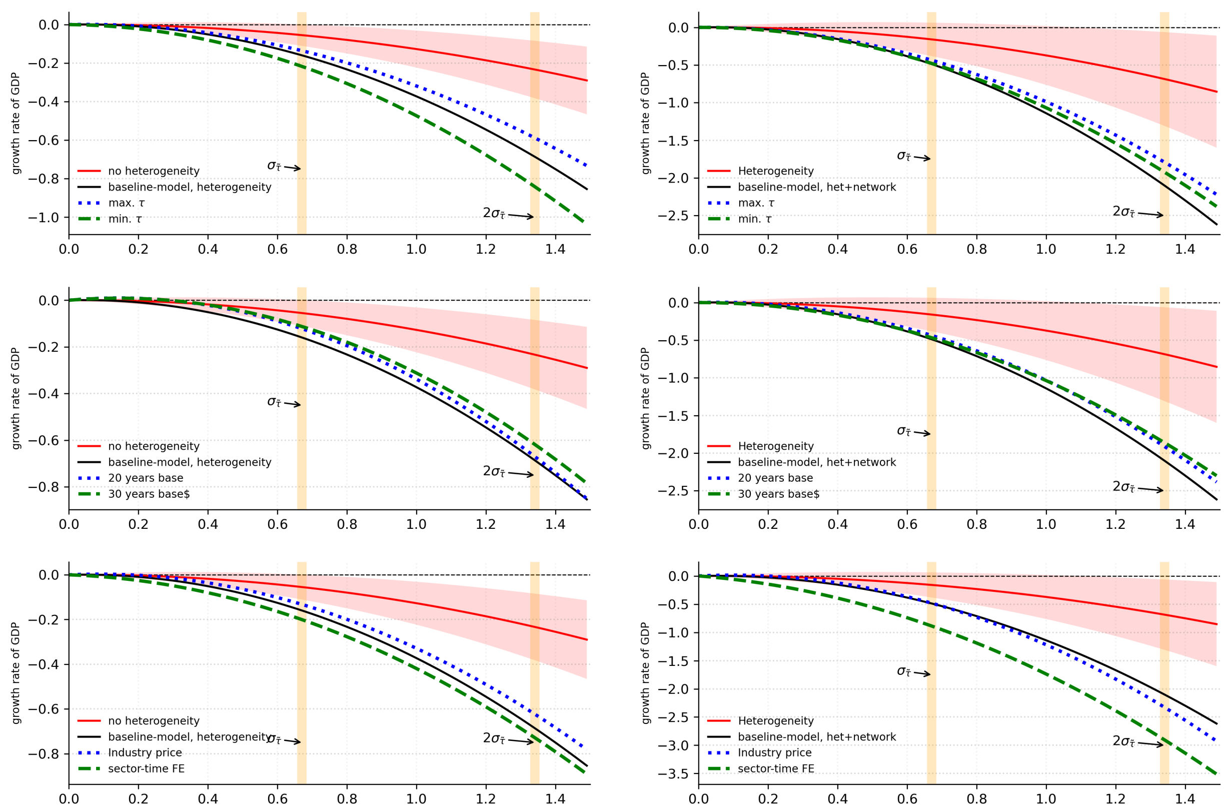
To test the robustness of my last conclusions, I calculated the estimates of the theoretical models in sections 3 and 4 using a total of seven different versions of their empirical counterparts. The first two alternative models change the choice of the temperature indicator τ from average temperatures to maximum temperature and minimum temperature, respectively. The second set of models varies the length of the rolling windows from which I compute the reference base $\bar{\tau}_{g,m,t}$, increasing it to 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. Therefore, I present 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 that estimates are robust to different

Figure 15. 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.

choices of temperature indicators and measurements of economic activity. Figure 15 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 or dashed green lines. In every case with can see that there results from the alternative models do not separate drastically from the baseline estimations and does not change my conclusions. Additional plots are added in appendix B

References

Acemoglu, Daron, Simon Johnson, and James A Robinson. 2002. "Reversal of fortune: Geography and institutions in the making of the modern world income distribution." *The Quarterly journal of economics*, 117(4): 1231–1294.

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.

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.

Deryugina, Tatyana, and Solomon M Hsiang. 2014. "Does the Environment Still Matter? Daily Temperature and Income in the United States." National Bureau of Economic Research Working Paper 20750.

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.

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, Kevin, Judy Lawrence, and Brendan Mackey. 2022. "IPCC sixth assessment report (AR6): climate change 2022-impacts, adaptation and vulnerability: regional factsheet Australasia."

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

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. In some cases, there are no available data for one of these sectors, in which case I input a value of 0. Surprisingly, in the accounts from 1963 to 1987, some observations register negative values of Gross Domestic Output per state. Whether this reflects put an explanation here, I consider them accounting issues and replace those values with zero.

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 allow 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 2 exemplifies this process.

Table 2. 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

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, equilibrium 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 3 shows the list of MSAs and regions from which BLS has records about specific CPIs and their starting dates.

Table 3. List of Metropolitan Statistical Areas and Regions (BLS)

Code Variable at BLS		Name	Full Name	Type	Initial period
Code 1	Code 2				
CUUR0100SA0	CUUS0100SA0	Northeast	Northeast		
CUUR0400SA0	CUUS0400SA0	West	West	Region	1966
CUUR0200SA0	CUUS0200SA0	Midwest	Midwest		
CUUR0300SA0	CUUS0300SA0	South	South		
CUURS35CSA0	CUUSS35CSA0	Atlanta	Atlanta-Sandy Springs-Roswell, GA		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	Metropolitan Statistical Area	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[13]:

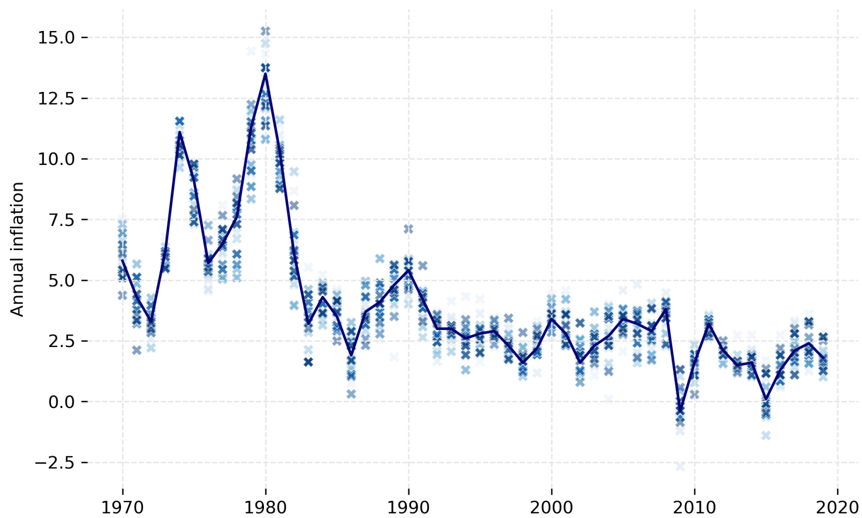
1. If none of the MSA in the list is situated in the specific state, then the regional CPI is chosen.

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

2. Then, when only one MSA is located in the specific state, the MSA's CPI is picked.
3. If multiple MSAs are included in a state, the state's CPI is computed as the average of the MSA's CPIs

Figure 16 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 16. 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 4 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

Table 4. 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.

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.

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 5 shows the list of the considered sectors, their industry, and whether they are treated as tradable or nontradable based on the CFS tables.

Table 5. 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

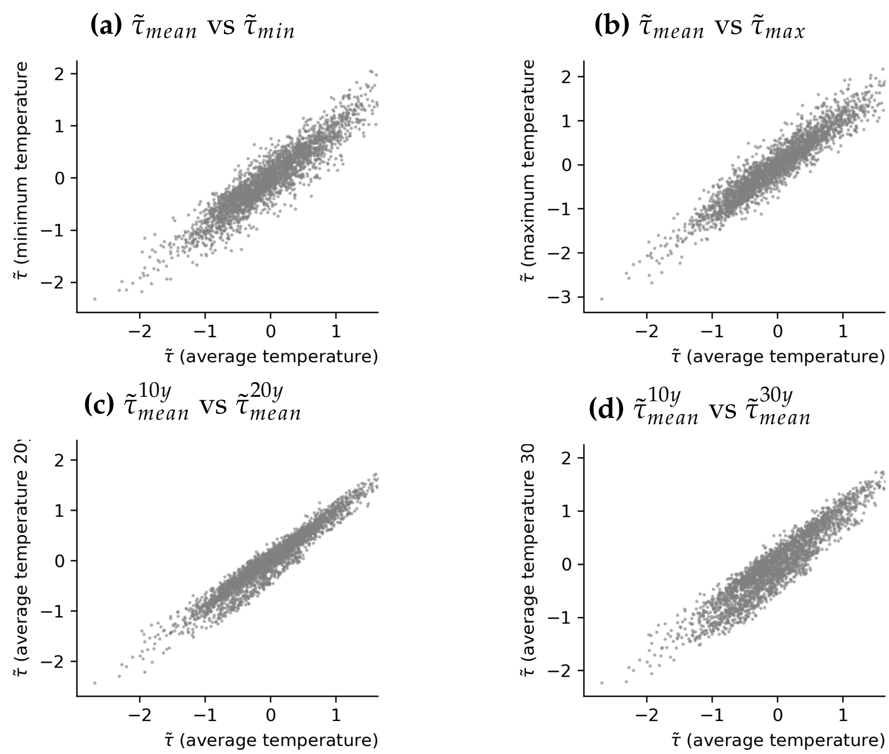
A.2 Temperature and other weather variables

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 ($\bar{\tau}^{(h)}_{s,t}$). 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[14] 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

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

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 17, 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.

Figure 17. Relation between temperature anomalies indicators



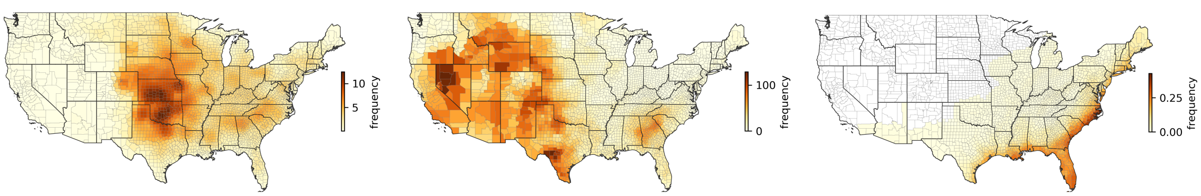
Note: Each panel depicts a scatterplot between temperature anomalies in the average temperature and other proxies for weather anomalies.

A.3 Weather-related natural disasters

In contrast to a small country, the large extension of the United States introduces differences in exposure to different natural disasters across states. This is clear in Figure 18 which shows the average frequency of hails (panel a), droughts (panel b), and hurricanes (panel b) by state. We can see that each type of disaster has a well-defined area of impact. Consequently, using the time series for individual disaster types might have limited explanatory power in my baseline regression. It brings difficulty since there is no clear way to combine different disaster types. Therefore, I need to rely on a series that incorporates these disasters into a unique risk measurement.

Figure 18. Disaster frequency by county

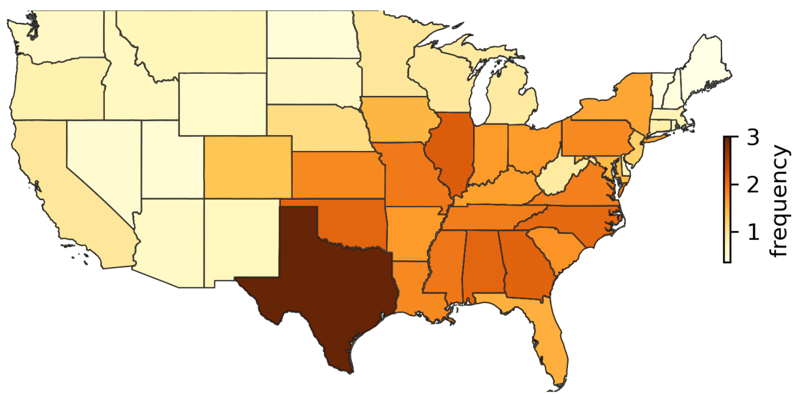
(a) Hails **(b)** Droughts **(c)** Hurricanes



Note: The figure plots the geographical distribution of the Natural Hazard Index (NHI). The yellow shade shows counties with very-small risk of natural hazards, and light green and green colors represent a small and moderate risk, respectively. Finally, blue and purple colors point to relatively high and high risk. **Source**: Federal Emergency Management Agency, Natural Hazard Index

Among the potential options there are two notable sources: the National Risk Index (NRI) released by the Federal Emergency Management Agency (FEMA) and the "U.S. Billion-dollar Weather and Climate Disasters" provided by the National Centers for Environmental Information (NCEI). The NRI was developed by FEMA in 2020 and uses comprehensive information about 18 different natural disasters to measure the risk that different counties face regards weather-related natural disasters. However, its limitation lies in the fact that this score lacks the time dimension, making impossible its direct use in my econometrical framework. Then, I choose the "U.S. Billion-dollar Weather and Climate Disasters" dataset as a proxy of the exposure to natural disasters. This dataset contains information on disasters that have caused economic losses larger than one billion dollars from 1980 to 2019. Figure 19 shows the average number of US-billion disasters that impact each state. Notably, the states of Texas, Illinois, Georgia, Alabama, and Oklahoma (84) reported the highest amount of disasters. In monetary terms, the US-billion disasters totalized a cost of around 4.5 trillion dollars, with more than half (2.4 trillion) caused by tropical cyclones mainly affecting Texas (224), Louisiana (250), and Florida (233). A potential drawback of this dataset is that a large disaster could [and mostly] affect several states in different measures but the data will consider that each state was equally affected.

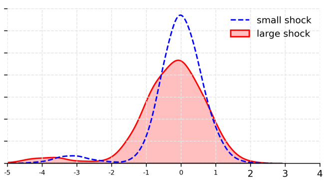
Figure 19. US billion-dollar disasters, frequency per state



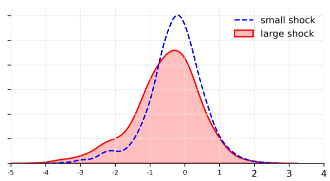
Appendix B Sensitivity analysis, additional figures

Figure 20. Distribution of $\mathcal{G}_{lg}(\tilde{\tau}^o)$, alternative models for **heterogeneous** responses

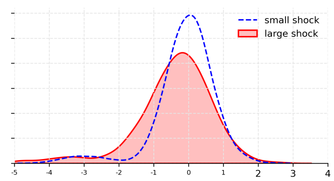
(a) max τ



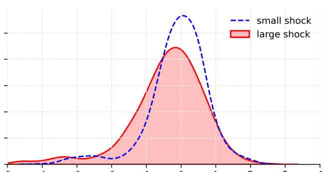
(b) min τ



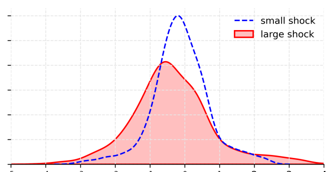
(c) 20-year τ



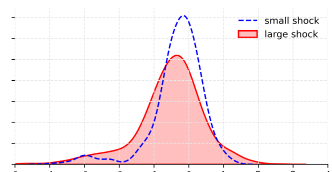
(d) 30-year τ



(e) Sectoral Price



(f) Sector-time FE



(g) Disaster

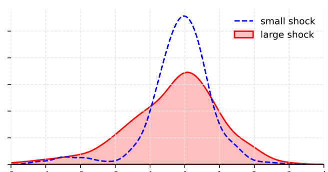


Figure 21. Aggregate effect of $\tilde{\tau}$, alternative models for **heterogeneous** responses

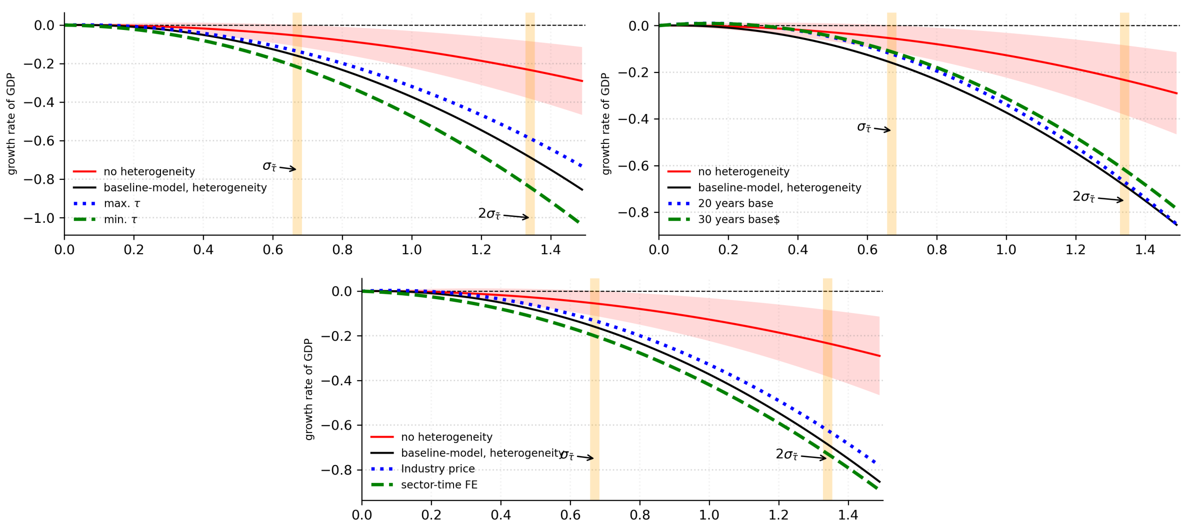
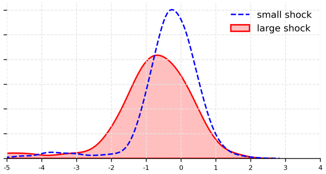
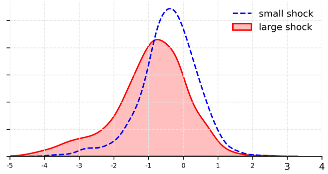


Figure 22. Distribution of $\mathcal{G}_{lg}(\tilde{\tau}^o)$, alternative models for **networks** responses

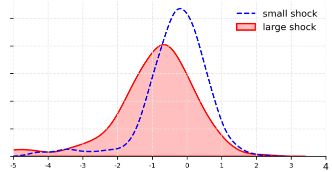
(a) max τ



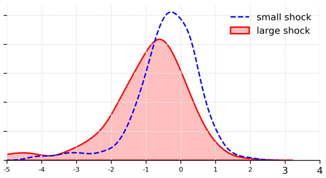
(b) min τ



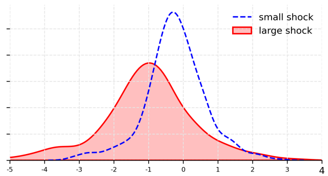
(c) 20-year τ



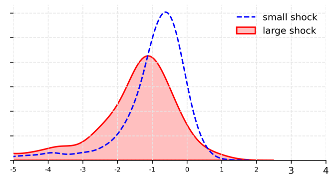
(d) 30-year τ



(e) Sectoral Price



(f) Sector-time FE



(g) Disaster

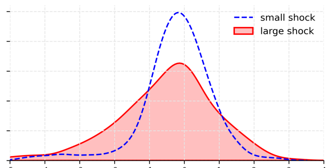
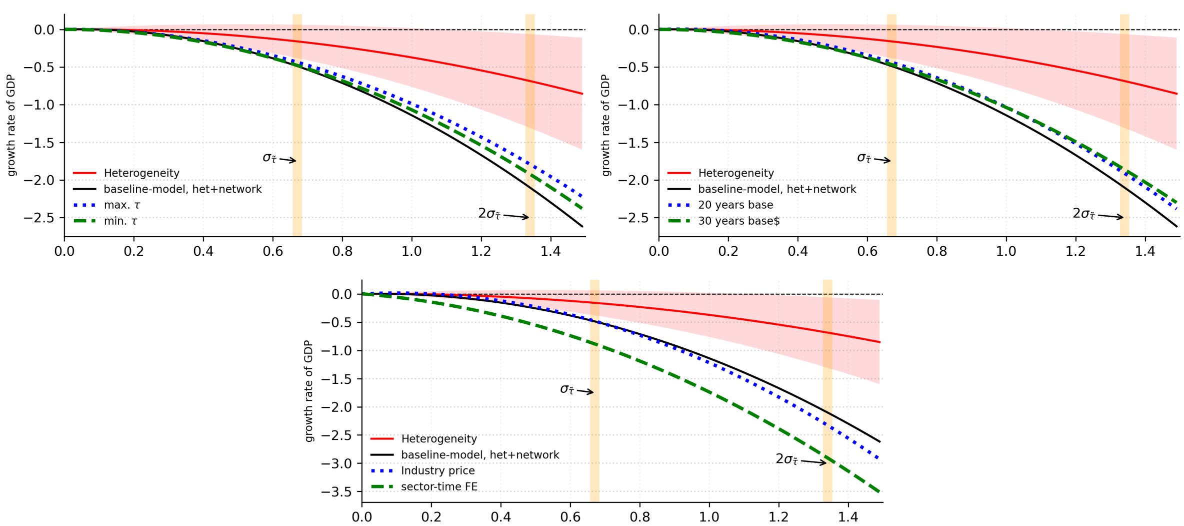


Figure 23. Aggregate effect of $\tilde{\tau}$, alternative models for **networks**

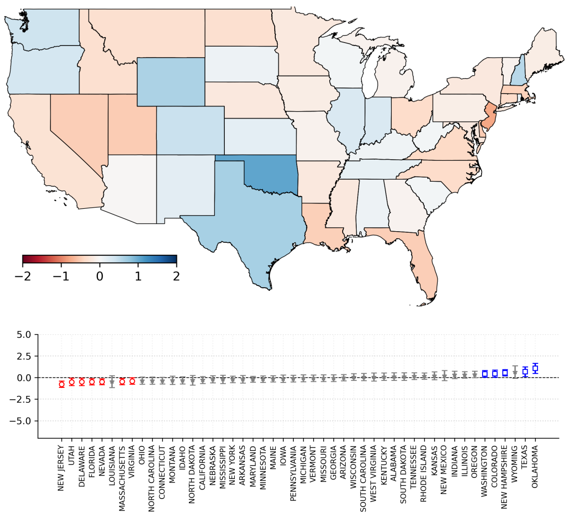


B.1 State-level results

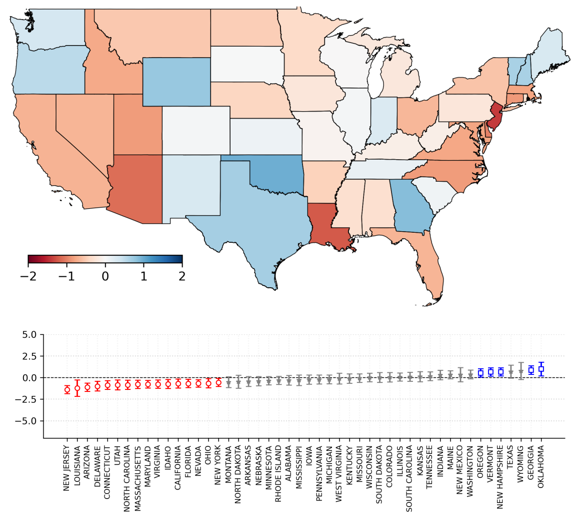
Figure 24. Impact -per unit Celsius- of $\tilde{\tau}$, model with maximum temperature

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

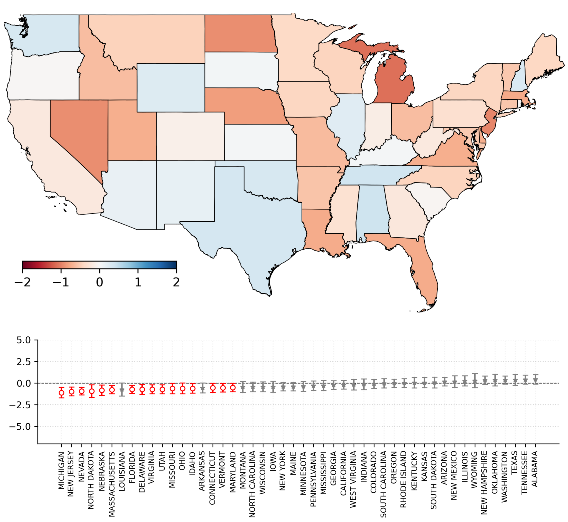


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

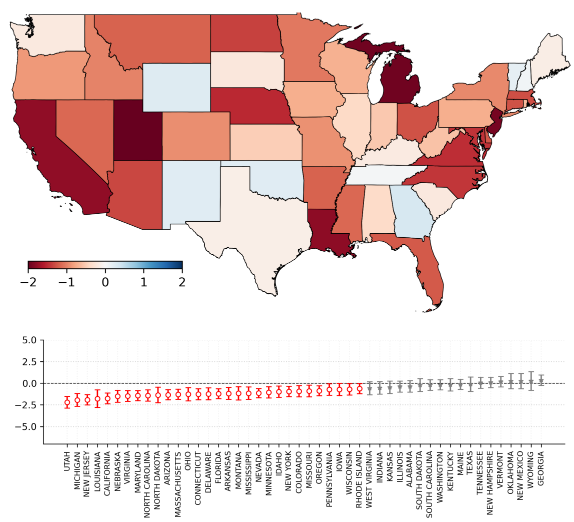
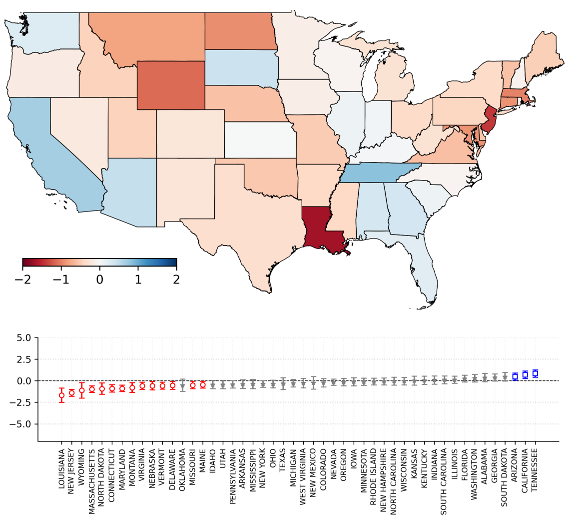


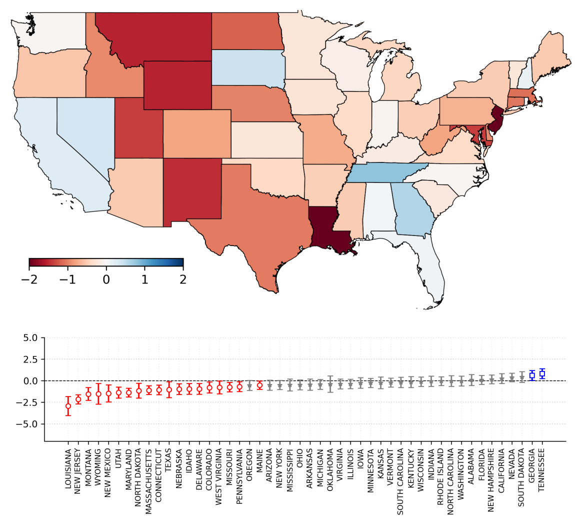
Figure 25. Impact -per unit Celsius- of $\tilde{\tau}$, model with minimum temperature

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

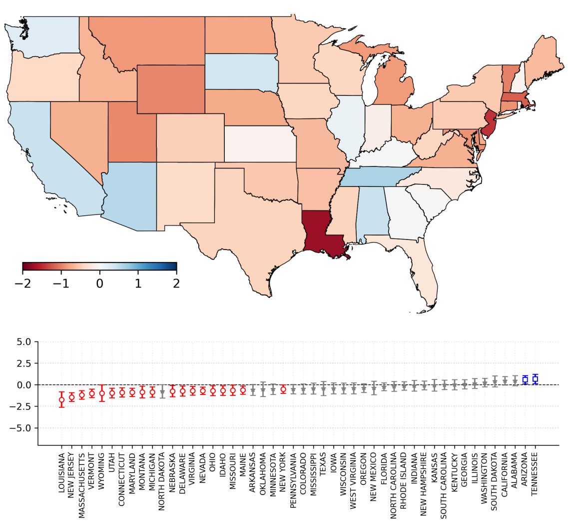


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

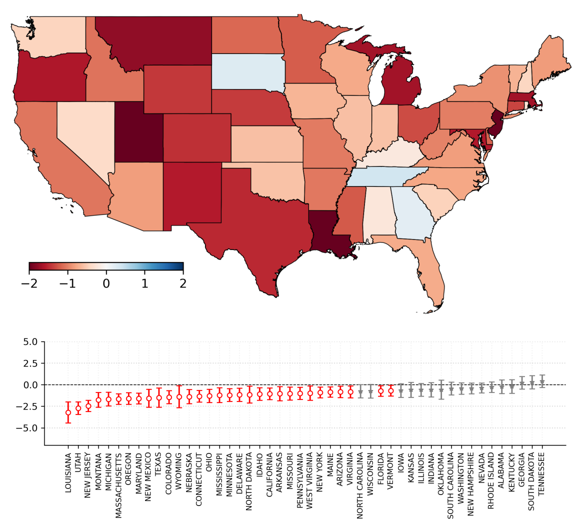
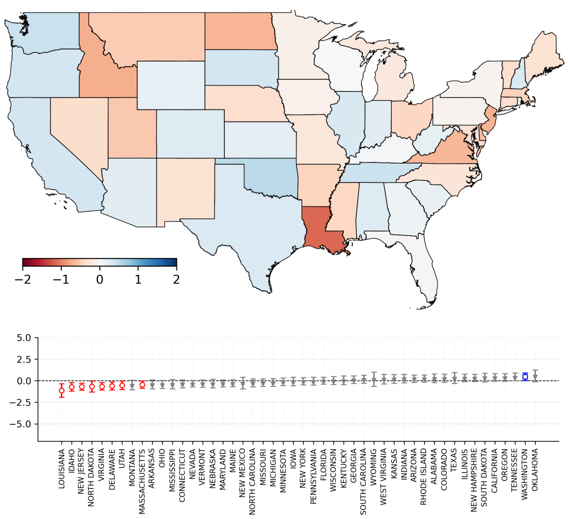


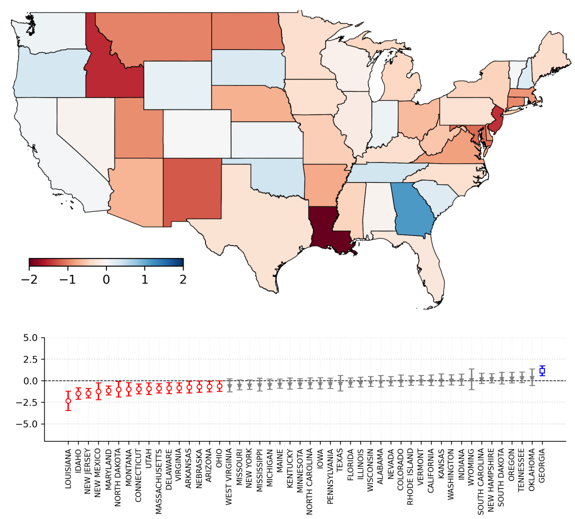
Figure 26. Impact -per unit Celsius- of $\tilde{\tau}$, model with 20-year reference base

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

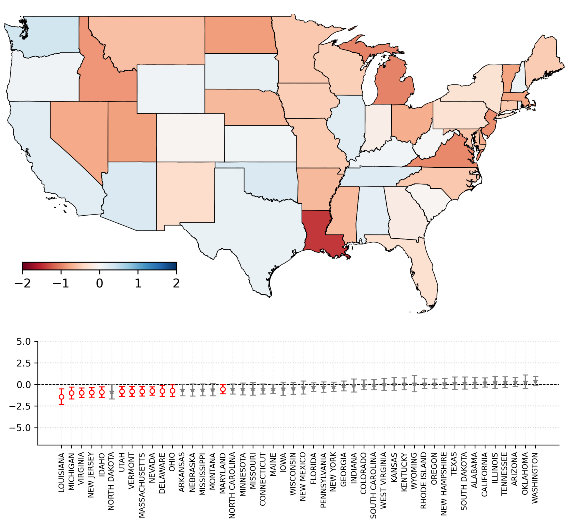


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

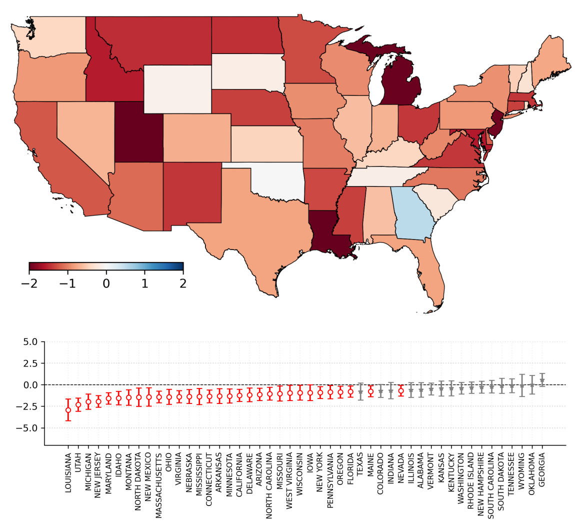
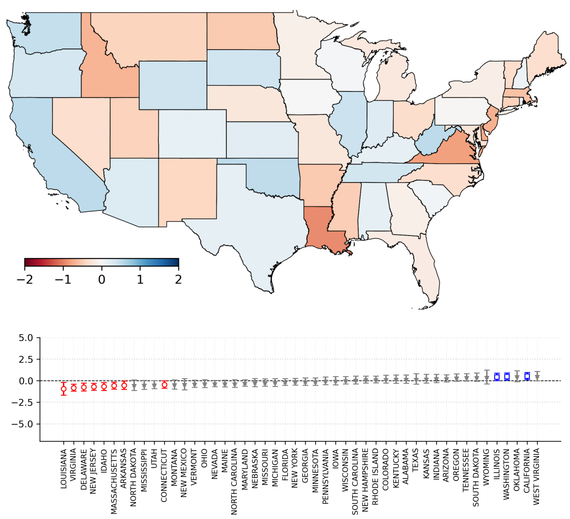


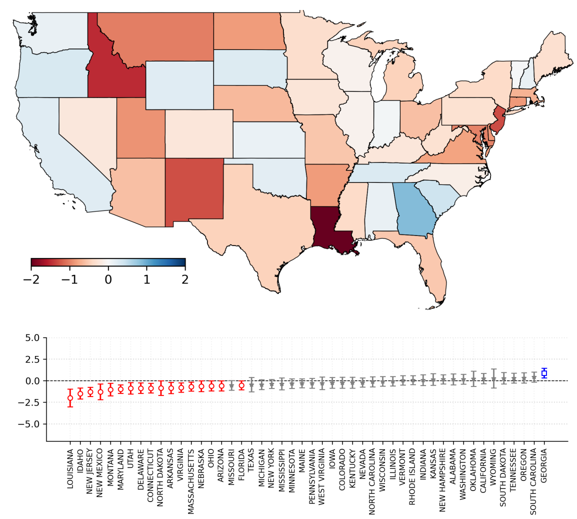
Figure 27. Impact -per unit Celsius- of $\tilde{\tau}$, model with 30-year reference base

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

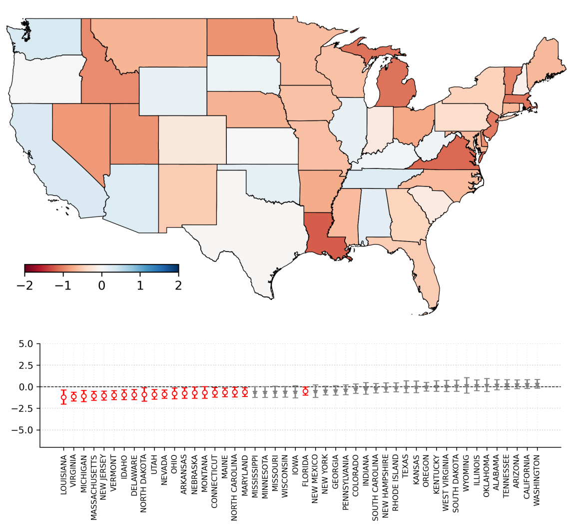


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

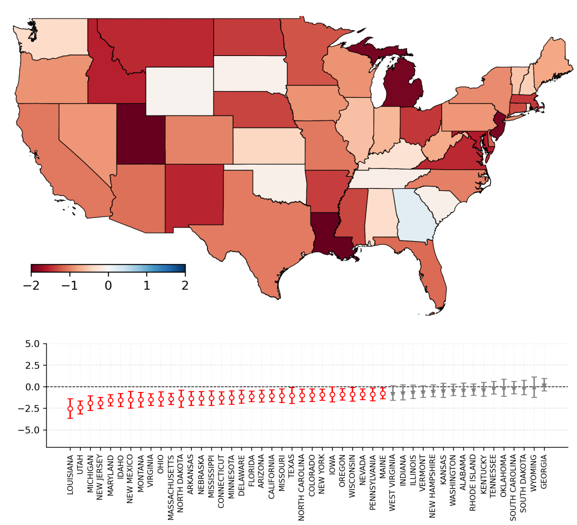
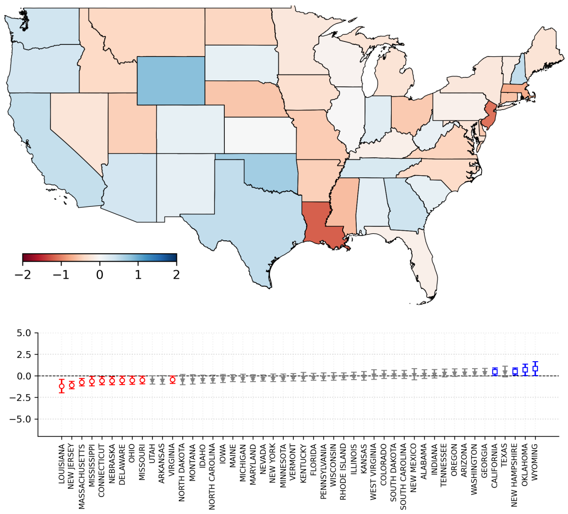


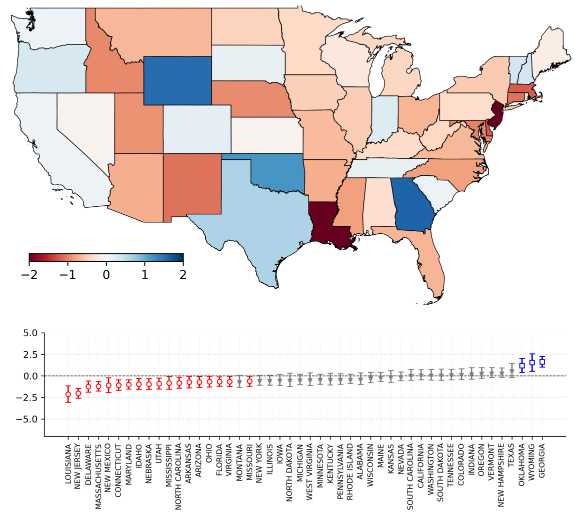
Figure 28. Impact -per unit Celsius- of $\tilde{\tau}$, model with industry-prices

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

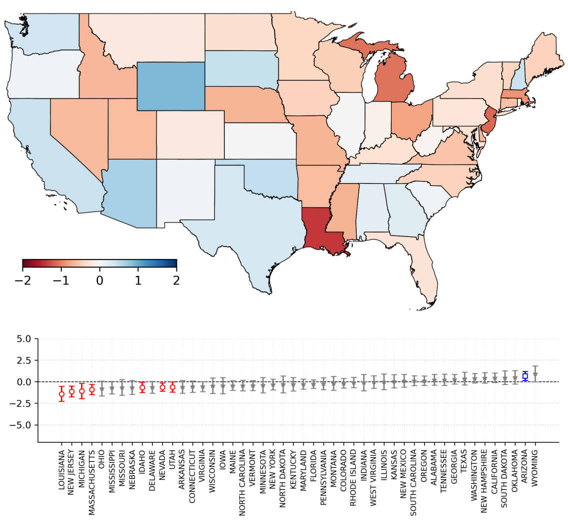


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

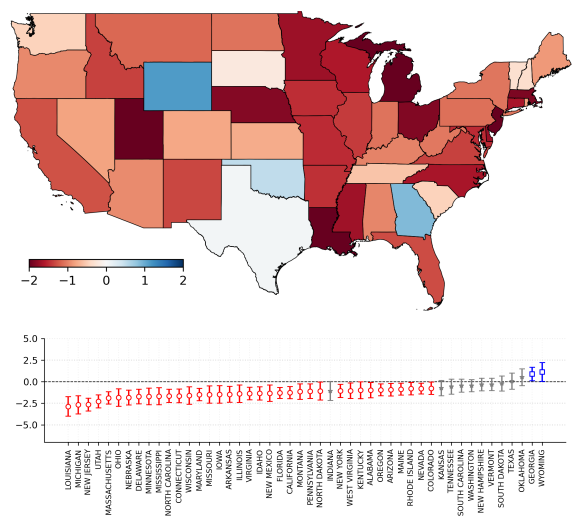
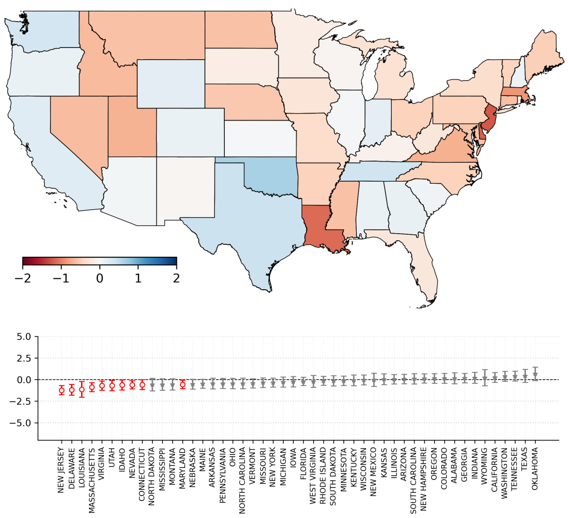


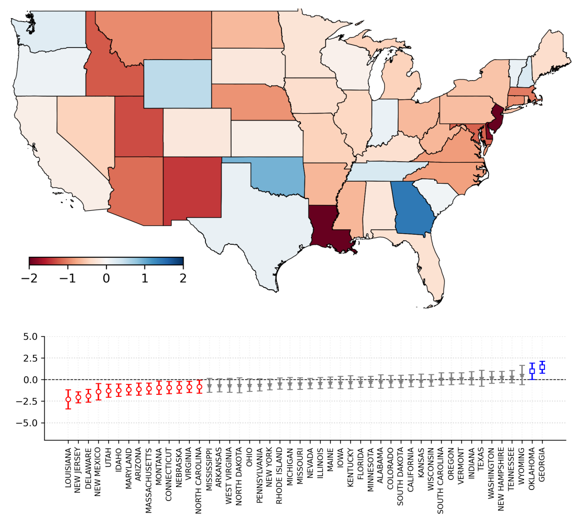
Figure 29. Impact -per unit Celsius- of $\tilde{\tau}$, model with sector-time FE

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

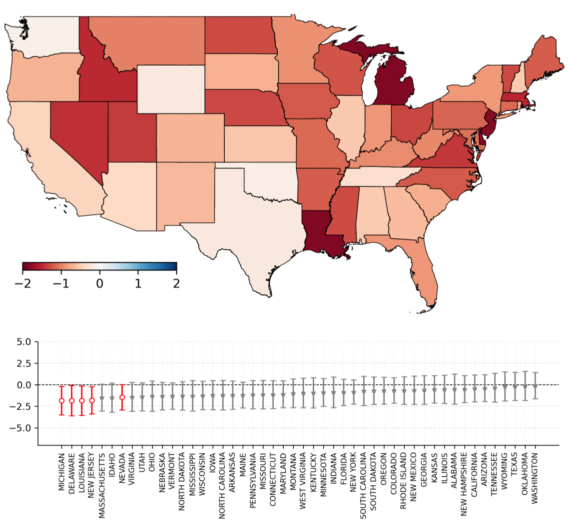


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

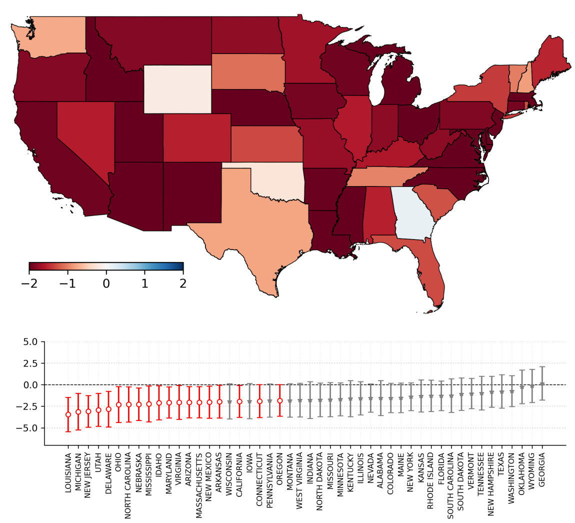
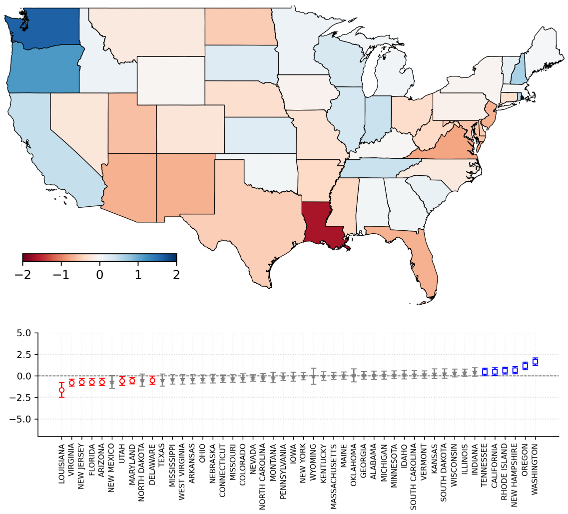


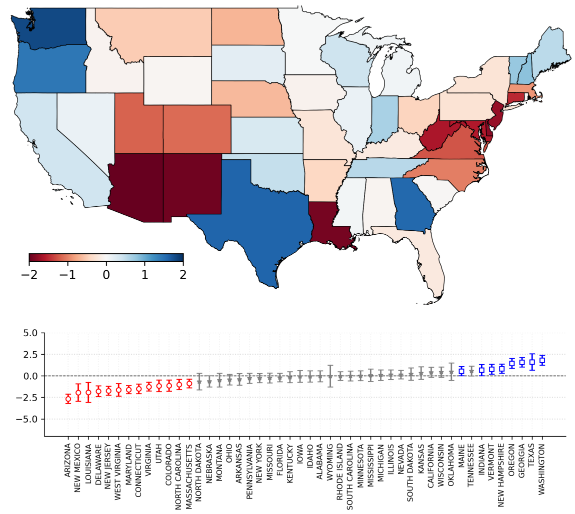
Figure 30. Impact -per unit Celsius- of $\tilde{\tau}$, model with disasters

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

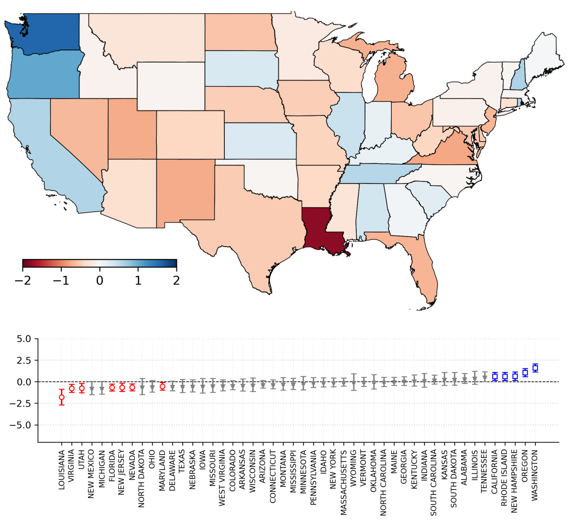


(a.1) large $\tilde{\tau}$

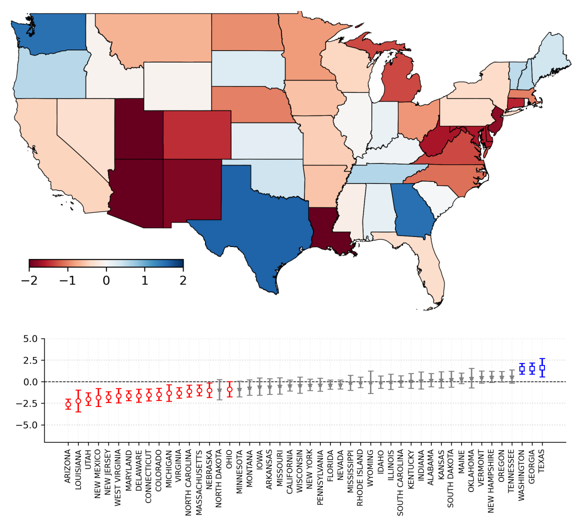


(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

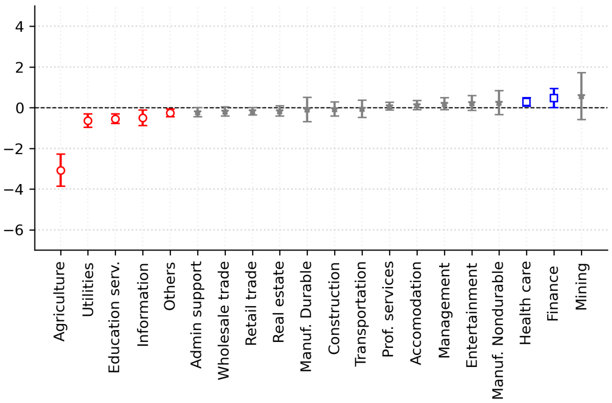


B.2 Industry-level results

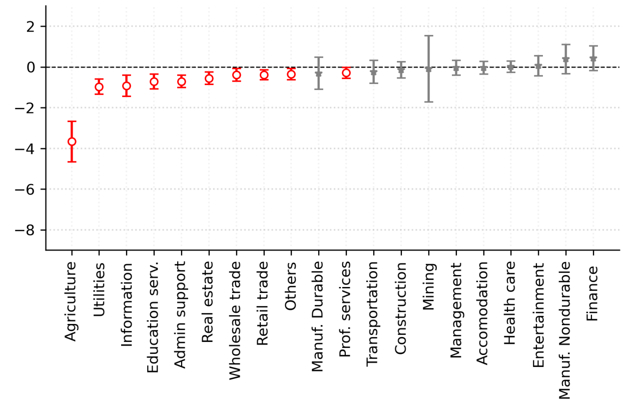
Figure 31. Impact -per unit Celsius- of $\tilde{\tau}$, model with maximum temperature

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

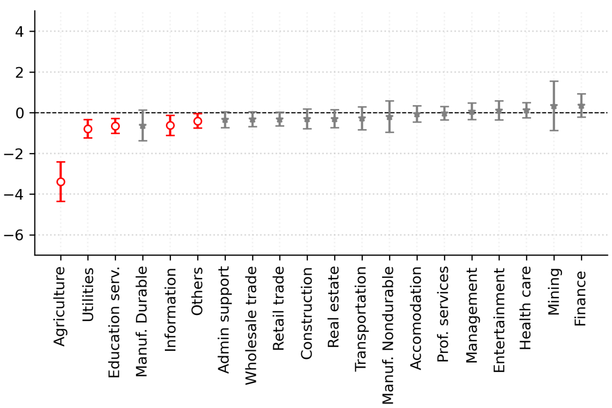


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

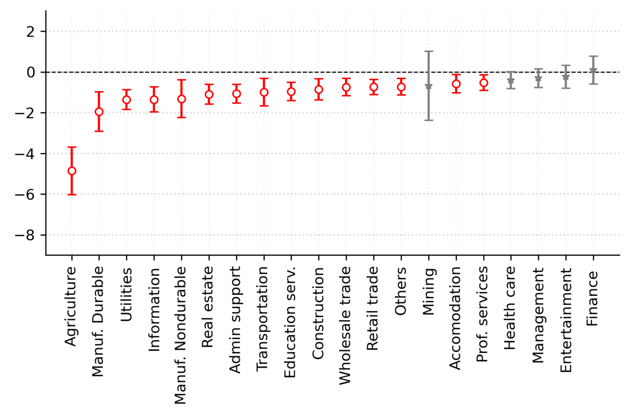
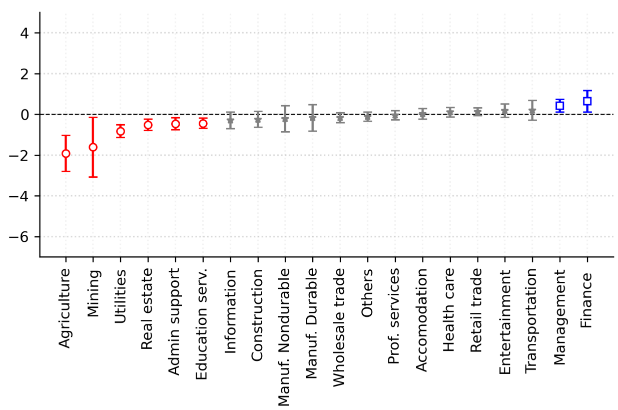


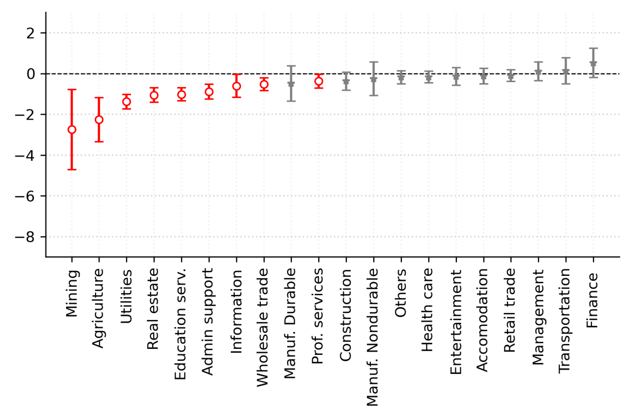
Figure 32. Impact -per unit Celsius- of $\tilde{\tau}$, model with minimum temperature

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

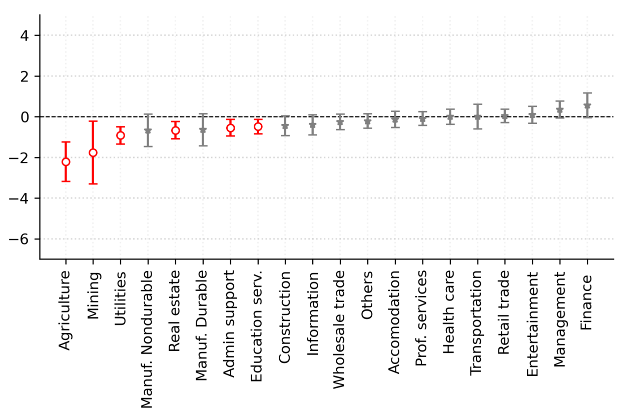


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

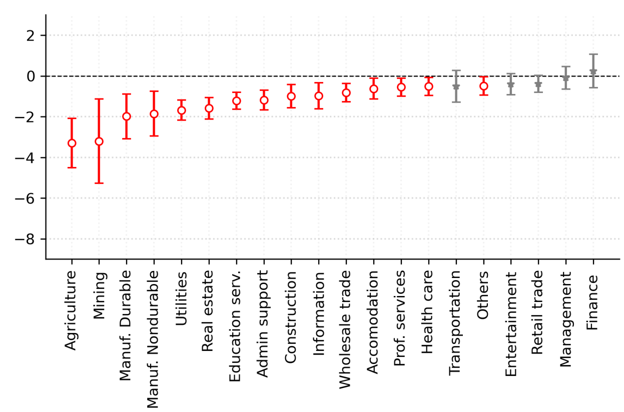
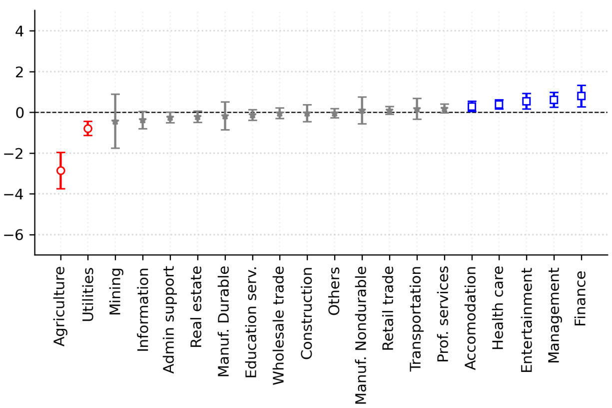


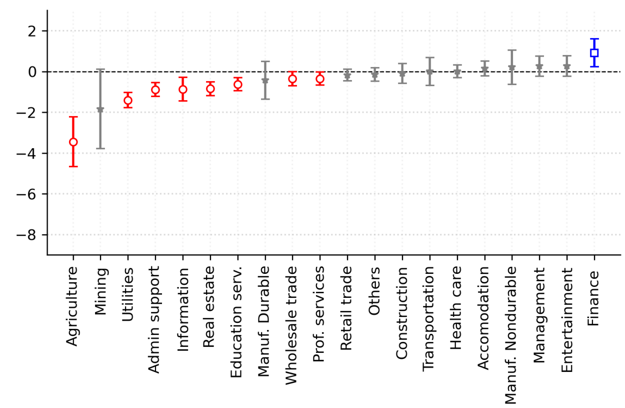
Figure 33. Impact -per unit Celsius- of $\tilde{\tau}$, model with 20-year reference base

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

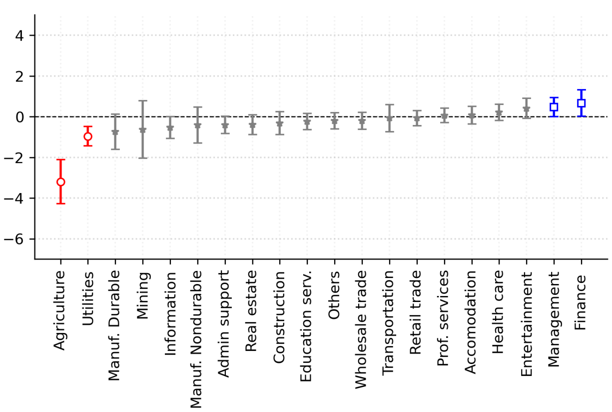


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

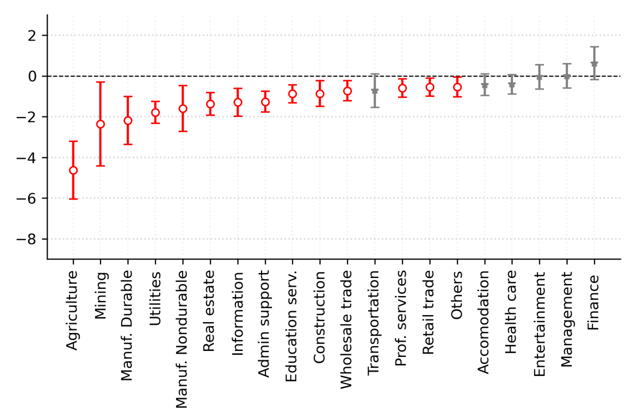
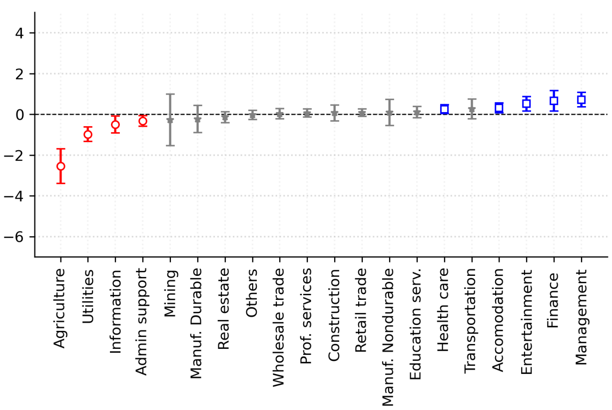


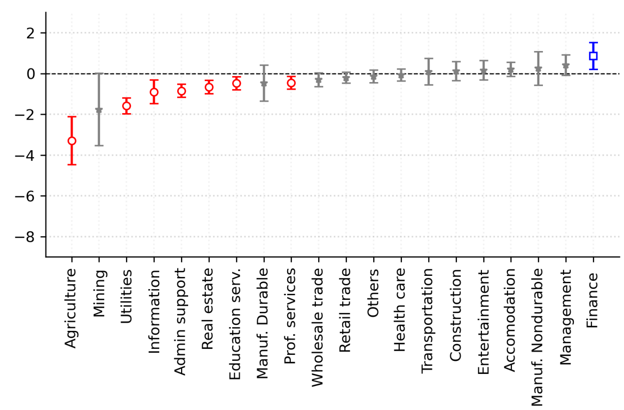
Figure 34. Impact -per unit Celsius- of $\tilde{\tau}$, model with 30-year reference base

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

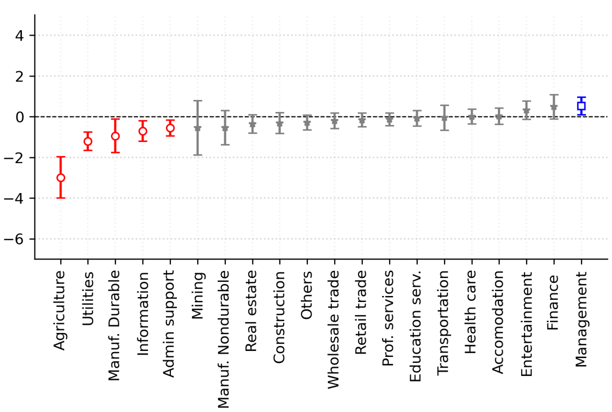


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

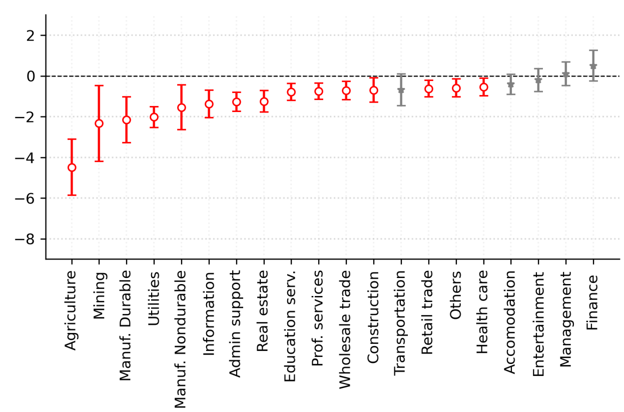
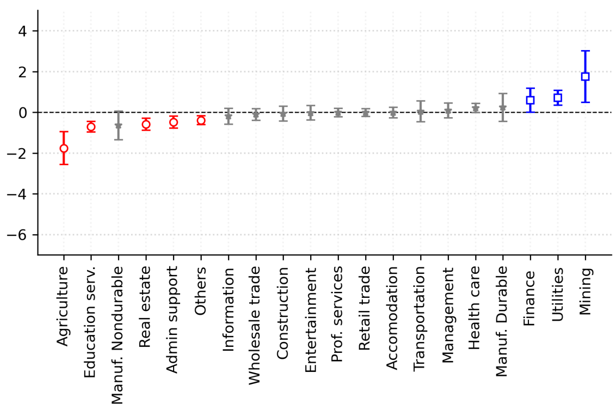


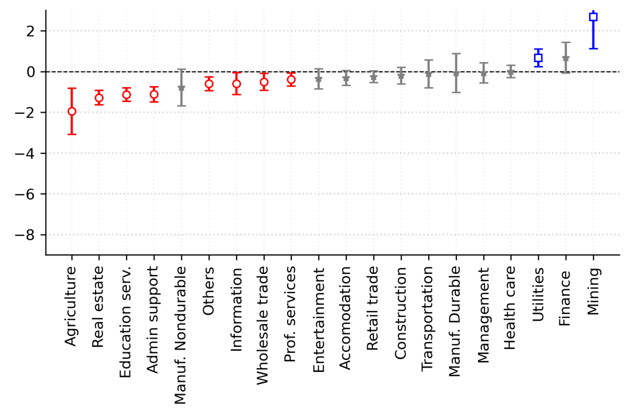
Figure 35. Impact -per unit Celsius- of $\tilde{\tau}$, model with industry-prices

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

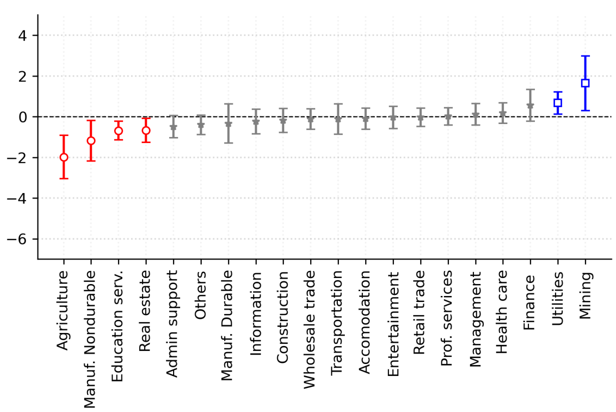


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

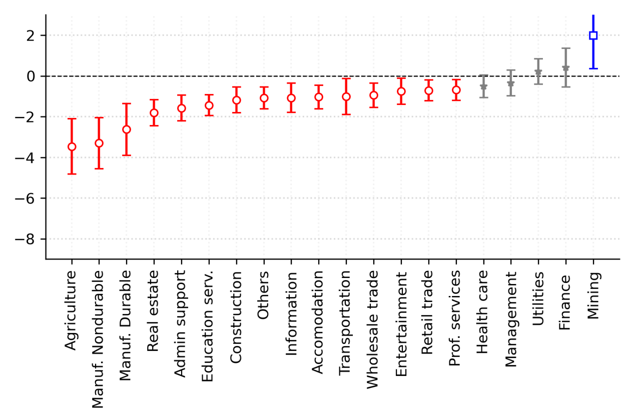
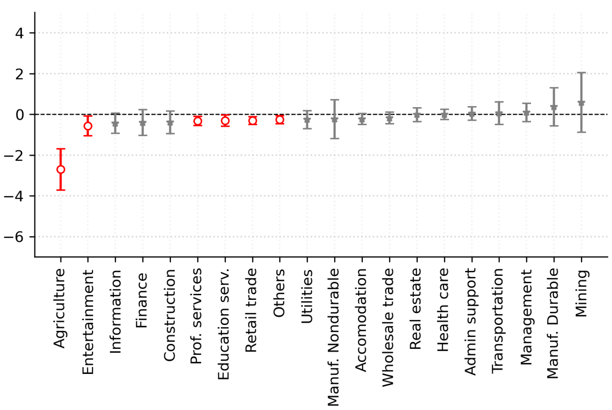


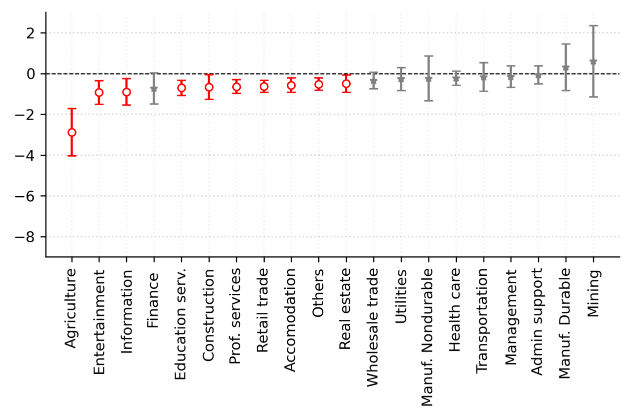
Figure 36. Impact -per unit Celsius- of $\tilde{\tau}$, model with sector-time FE

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

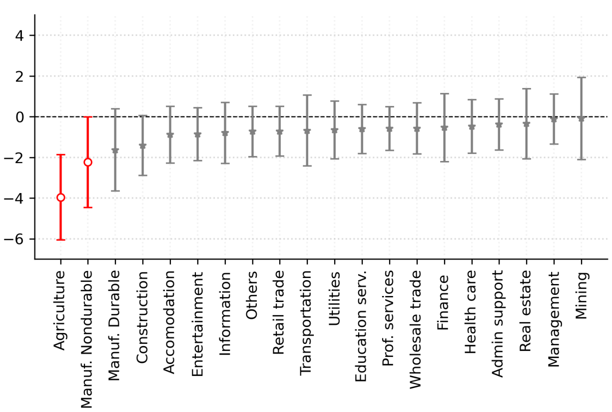


(a.1) large $\tilde{\tau}$



(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$

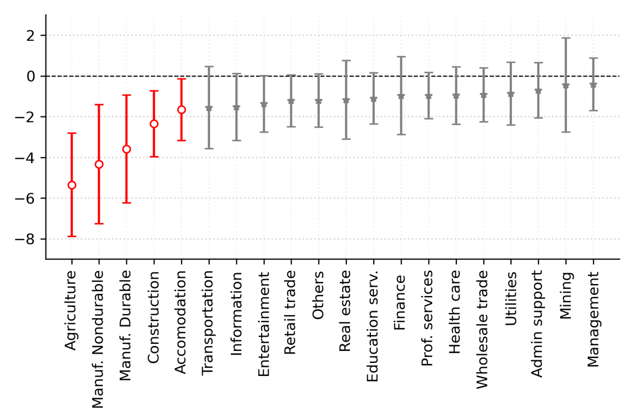
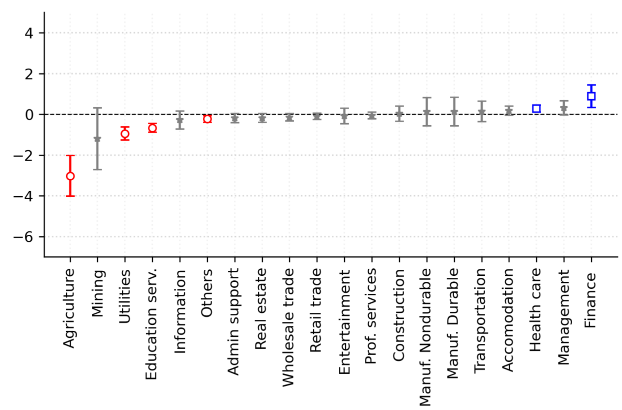


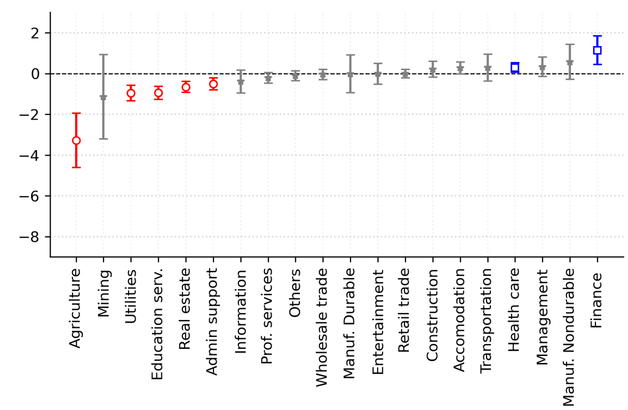
Figure 37. Impact -per unit Celsius- of $\tilde{\tau}$, model with disasters

(a) Model with sector and state heterogeneity

(a.1) small $\tilde{\tau}$

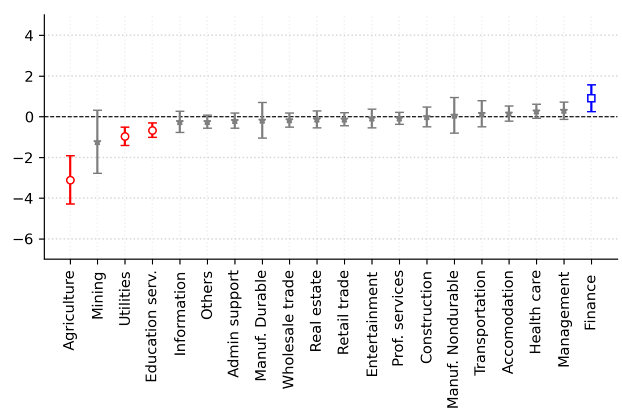


(a.1) large $\tilde{\tau}$

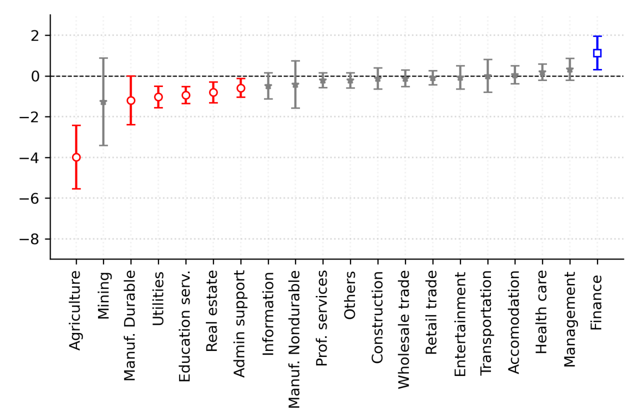


(b) Model with heterogeneity and networks

(b.1) small $\tilde{\tau}$



(b.2) large $\tilde{\tau}$



Appendix C Additional derivations

C.1 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. The new production function for intermediate goods is:

$$y_n^j = z_n^j(\tilde{\tau}_n) \left(l_n^j\right)^{\tilde{\alpha}_n^j} \prod_m \left(x_{nm}^j\right)^{a_{nm}^j} \tag{29}$$

where the pair $x_{n,m}$ is the amount of final goods m that the sector y_n^j buys to use them as materials. The constant returns to scale assumption implies $\alpha_n + \sum_m a_{nm} = 1 \, \forall \, n$. The optimality conditions for the intermediate-good firms are:

$$a_{nm}^j = \frac{p_m x_{nm}^j}{p_n^j y_n^j} \tag{30}$$

$$\alpha_{nm}^j = \frac{w l_n^j}{p_n^j y_n^j} \tag{31}$$

let g_n^j denote the real value added (or real GDP) by the sector j located in the region n. Since $g_n^j = \frac{w l_n^j}{p_n^j}$, we can use equation31 express the fluctuation of the real GDP by sector-state as:

$$d \ln g_n^j = d \ln y_n^j$$

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 30, we obtain the following relation:

$$x_{nm}^j = a_{nm}^j b_n^j \frac{\beta_n}{\beta_m} \frac{c_m}{c_n} y_n \tag{32}$$

that can be introduced in the market clearing condition $y_n = c_n + \sum_m \sum_j x^j_{mn}$ to reach the following result:

$$\frac{y_n}{c_n} = 1 + \sum_m \left(\frac{\beta_m}{\beta_n} \sum_j a^j_{mn} b^j_m \right) \frac{y_m}{c_m} \tag{33}$$

Equation 33 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, implying that $d \ln y_n = d \ln c_n$.

From equation 32:

$$d \ln x^j_{nm} = d \ln c_m = d \ln y_m$$

That can be introduced into the production function of the intermediate firms.

$$\begin{aligned}
d \ln y^j_n &= d \ln z^j_n(\tilde{\tau}_n) + \alpha d \ln l^j_n + \sum_m a^j_{nm} d \ln x^j_{nm} \\
d \ln y^j_n &= d \ln z^j_n(\tilde{\tau}_n) + \alpha d \ln l^j_n + \sum_m a^j_{nm} d \ln y_m \\
d \ln y^j_n &= d \ln z^j_n(\tilde{\tau}_n) + \alpha d \ln l^j_n + \sum_m a^j_{nm} \sum_l b^i_m d \ln y^i_m \\
d \ln g^j_n &= d \ln z^j_n(\tilde{\tau}_n) + \alpha d \ln l^j_n + \sum_m a^j_{nm} \sum_l b^i_m d \ln g^i_m \\
d \ln g^j_n &= d \ln z^j_n(\tilde{\tau}_n) + \alpha d \ln l^j_n + \sum_{m,i} a^j_{nm} b^i_m d \ln g^i_m
\end{aligned} \tag{34}$$

From condition 31, and then including optimality condition of final good producer and households

$$
\begin{aligned}
a^j_{nm} p^j_n y^j_n &= w l^j_n \\
a^j_{nm} b^j_n p_n y_n &= w l^j_n \\
\underbrace{a^j_{nm} b^j_n \beta_n PY}_{constant} &= w l^j_n \\
PY \sum_n \sum_j a^j_{nm} b^j_n \beta_n &= wL \\
\frac{l_i}{L} &= \text{constant}
\end{aligned}
\tag{35}
$$

It means that at equilibrium $d \ln l^j_n = 0$. Therefore

$$
\begin{aligned}
d \ln g^j_n &= d \ln z^j_n(\tilde{\tau}_n) + \sum_{m,i} a^j_{nm} b^i_m d \ln g^i_m \\
\ln \boldsymbol{g} &= \Psi d \ln \boldsymbol{z} = (I - A)^{-1} d \ln \boldsymbol{z}
\end{aligned}
\tag{36}
$$

where $\ln \boldsymbol{g} = \left[d \ln g^1_1, d \ln g^2_1, ...\right]^T$ is a column vector composed of the sector-state real GDP growth rates. The matrix A collects all the coefficient $b^j_m a^j_{nm}$ 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 shock z^j_n has in all the other sectors y^i_m of the economy. Finally, this expression can be write as:

$$
\mathrm{d} \ln g^j_n = \underbrace{\mathrm{d} \ln z^j_n(\tau_n)}_{\text{own effect}} + \overbrace{\sum_{i,m} (\psi^{ji}_{nm} - \mathbf{1}_{n=m,j=i}) \mathrm{d} \ln z^i_m(\tau_m)}^{\text{network effect}}
\tag{37}
$$