From Micro-level Weather Shocks to Macroeconomic Impacts

Anthony R. Harding*
Kennedy School
Harvard University

November, 2022

Abstract

I develop a general equilibrium model of the macroeconomic impacts of microeconomic weather shocks accounting for production networks and non-linearities in production. In the model, weather shocks *directly* affect the productivity of *local* producers. I find a closed-form solution for the general equilibrium of the model and use it to draw insights. The first insight is that, though weather shocks are local, in the presence of networks and shared labor markets, *direct* effects from weather shocks can generate *indirect* impacts throughout the economy. This suggests that empirical estimates that relate economic outcomes, such as income, to weather variations can be biased if they do not account for these spillovers. Second, I show that non-linearities in production from complementarities can generate non-linearities in the aggregation of local weather shock impacts. This depends critically on variability in microeconomic impacts. Third, I show that labor reallocation can moderate the aggregate impacts of weather shocks, but again only if there is variability in microeconomic impacts. Using an empirical setting of 14 sectors across counties spanning the continental United States from 2001 to 2017, I empirically constrain the economic importance of my theoretical findings. I find that, given inherent variability in weather shocks and in the response of industries to weather shocks, accounting for non-linearities in aggregation increase the aggregate economic costs of weather impacts in the US economy by 33%. I find that free labor reallocation reduces these aggregate impacts by 10%. Accounting for local variability and non-linearities is not just theoretically relevant, its economically significant.

JEL Codes: O44, O47, Q54, Q56, D57

Keywords: Climate Economics, Economic Growth

*tonyharding@hks.harvard.edu. I thank Christopher Blackburn, Juan Moreno-Cruz, Matthew Oliver, and participants of EGU 2021 and AERE 2021 for comments and feedback.

1 Introduction

Weather is both local and variable. For a given day, a worker in Phoenix, AZ could experience a hot and sunny 90°F day while a worker in Boston, MA experiences a cold and rainy 45°F day. The hot weather may affect the productivity of the worker in Phoenix, but it does not directly affect the worker in Boston. Similarly, the cold and rainy weather may affect the productivity of the worker in Boston, but it does not directly affect the worker in Pheonix. Yet, as I argue in this paper, there can be *indirect* effects through networks in the larger economy. Accounting for these network effects and how they interact with the inherent variability of weather has important implications for aggregate climate impacts and for climate policy.

To reflect this reality of the problem, I develop a general equilibrium model where weather shocks are embedded in local production technology. The productivity of each producer in a given region is a function of the weather in that region only. This means that the productivity of producers in Phoenix is only a function of the weather in Phoenix, not Boston. Further, the relationship between weather and production technology can vary across sectors. The agricultural sector in Phoenix may respond differently to weather shocks than the finance industry.

This model builds on recent advances in macroeconomic theory examining the role of production networks (Acemoglu et al., 2012; Baqaee and Farhi, 2019; Blackburn and Moreno-Cruz, 2021). In the presence of production networks, I demonstrate that local weather shocks can both propagate – causing indirect impacts elsewhere in the economy – and amplify as heterogeneous weather shocks interact. Leveraging the closed-form equilibrium of this model and analyzing the aggregate impacts of microeconomic weather shock impacts, I draw several important theoretical findings.

First, while the direct effects of weather shocks are defined to be local, I show that these shocks can have indirect spillover effects throughout the economy in equilibrium. When a weather shock decreases the productivity of an industry in one locale, this increases the price of their output and lowers wages. This increase in prices is then, in turn, passed on to consumers of their output as intermediate inputs in their production process. This process propagates weather shock impacts through the economy. Overlooking these spillovers can lead to imprecise partial equilibrium estimates of impacts and could bias empirical estimates of the relationship between weather shocks and economic outcomes.

Second, I turn to the aggregate impact of microeconomic weather shock impacts throughout an economy. I show that non-linearities in production from complementarities can interact with heterogeneity in microeconomic impacts to affect aggregate impacts. When industries are complementary and weather shocks are heterogeneous, non-linearities amplify negative weather shock impacts and dampen positive weather shock impacts.

Third, these non-linearities in production also provide a channel through which economic systems can act as an adaptation mechanism. When microeconomic impacts of weather shocks are heterogeneous across the economy, factors of production can reallocate across the economy away from less productive producers towards more productive producers, moving factor inputs to where they are most productive. When there are complementarities to production, this reallocation amplifies positive weather shocks and dampens negative weather shocks.

To examine the economic importance of these theoretical findings, I turn to an empirical setting in the continental United States, considering 14 NAICS industry classifications across all 3,080 counties from 2001 to 2017. To identify a relationship between weather shocks and productivity, I use panel data fixed effects methods to estimate a non-linear relationship between productivity growth and both temperature and precipitation. I flexibly allow for the responses to vary across industry classifications and find evidence of heterogeneity across industries in both the size and shape of these relationships.

I use these empirically estimated response functions to estimate the aggregate impacts of microeconomic weather shock impacts across the economy over the sample period according to my theoretical findings. In a naive estimate, I find that weather shock impacts have a predominantly negative impact ranging up to an annual loss of 0.5% of GDP in a given year and a cumulative loss over the sample period of around $350 billion. Decomposing these aggregate impacts, I find evidence of considerable heterogeneity in both the sign and magnitude of weather shock impacts across both industries and space.

Next, I examine whether this heterogeneity in microeconomic impacts interacts with non-linearities in production to meaningfully affect aggregate impacts. Cumulative over the sample period, I find that accounting for these non-linearities in accordance with my theoretical findings raises aggregate losses by 33%. This indicates that accounting for non-linearities at the microeconomic scale is economically important in the climate change problem. Further, I find that allowing for factor reallocation recovers around 10% of these aggregate losses. This provides evidence that adjustments in economic systems can be an important adaptation mechanism.

This work contributes builds on a long literature on the aggregate impacts of microeconomic fluctuations or growth accounting. Building on seminal works by the likes of Hulten (1978) and Long and Plosser (1983), recent research has revisited the growth accounting problem to highlight the importance of microeconomic structural characteristics. Gabaix (2011) and Acemoglu et al. (2017) highlight the role of dispersion in the size of firms in generating macroeconomic fluctuations. Atalay (2017), Baqaee and Farhi (2019), and others highlight the importance of production network characteristics. This paper contributes to this literature by bringing its seminal models and insights to the climate change economics problem. In particular, this paper shows how non-linearities in the climate change problem can interact and amplify important non-linearities identified in the aggregation problem.

This paper also contributes to theoretical and empirical work in climate change economics, analyzing the role of market-based adjustments as an adaptation mechanism. Insights about reallocation as an adaptation mechanism derived from this framework are consistent with theoretical and empirical findings for trade following changes in agricultural productivity (Costinot et al., 2016; Gouel and Laborde, 2021) and labor reallocation between agriculture and manufacturing due to changes in labor productivity (Colmer, 2018). Closer to this paper is a concurrently growing literature on climate impacts in dynamic spatial general equilibrium models. Rudik et al. (2021) and Cruz and Rossi-Hansberg (2021) use these models to explore the role of market-based adaptation through trade and migration in climate change impacts. These models require strict modeling assumptions to allow for inversion of the model; the assumption of Cobb-Douglas production technologies is particularly relevant in this setting. This paper contributes to this literature by relaxing these assumptions in a closed-form general equilibrium model, highlighting the importance of the interaction between micro-level heterogeneity and non-Cobb-Douglas production technologies.

The insights drawn from this paper contribute to the empirical climate econometric literature. This literature has predominantly focused on distinctly microeconomic or macroeconomic scales. For example, empirical microeconomic studies estimate the effect of weather on productivity at the level of counties, firms, or even individuals (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Graff Zivin and Neidell, 2014; Burke and Emerick, 2016; Colmer, 2018; Park et al., 2020). Alternatively, macroeconomic empirical studies estimate response at the level of countries (Dell et al., 2012; Burke et al., 2015; Letta and Tol, 2019). This paper provides both theoretical and empirical evidence emphasizing the importance of using high-resolution data to capture the true underlying relationships and justification for focusing on economic primitives to avoid bias from spillovers. Close to this, Damania et al. (2020) shows that spatial aggregation can wash out important micro-level variation, attenuating the effect of precipitation on growth.

The paper proceeds as follows. In Section 2 I present a general equilibrium theoretical framework that introduces weather shocks through local labor productivity. In Section 3 I provide a closed-form solution to the equilibrium of the model and describe how to construct estimates of the macroeconomic impacts of weather shocks from microeconomic estimates and highlight the importance of heterogeneity. In Section 4 I describe the data in the empirical application of the theoretical model and estimate the microeconomic response functions between weather and growth. In Section 5 I apply the theoretical findings to construct estimates of the aggregate impacts from microeconomic weather impacts. In Section 6, I provide comparative analyses where I remove different sources of micro-level heterogeneity to demonstrate their importance. In Section 7 I conclude.

2 Theoretical Framework

The model is a static general equilibrium model of an economy that follows the multi-sector general equilibrium model of Long and Plosser (1983) and Acemoglu et al. (2012), augmented to capture the regional aspects of production rather than just industry aggregates. The economy is composed of two types of agents, a representative consumer and many producers. The representative consumer consumes final goods to maximize their utility. Each producer in the model represents an industry producing a region-specific good or service. Producers combine labor inelastically supplied by the representative consumer and intermediate inputs from other producers to minimize the cost of production. Output is either used by other producers as intermediate inputs to their production or consumed by the representative consumer.

I extend the model to incorporate local weather shocks. To capture the sources of heterogeneity found in empirical studies of climate impacts (Graff Zivin and Neidell, 2014; Park et al., 2020), weather in a given region directly affects the labor productivity of industries in that region. This means that a hot day in Phoenix, AZ will only *directly* affect labor productivity in Phoenix. Industries within each region are also flexible in their response to weather. The hot day in Phoenix could have a different effect on productivity in the construction industry than in the finance industry.

2.1 Setup

2.1.1 Households

The preferences of the representative consumer are characterized as a constant elasticity of substitution (CES) utility function U. Given income M received for inelastically supplied labor, $\bar{L}$, and prices, p_{ir}, the representative consumer chooses a consumption bundle c_{ir} of final goods and services across industries $i \in \{1, ..., N\}$ in regions $r \in \{1, ..., R\}$ to maximize utility. This constrained maximization problem is given as

$$
\begin{aligned}
U(c_{11},...,c_{NR}) &= \max_{c_{11},...,c_{NR}} \left[\sum_{i=1}^{N} \sum_{r=1}^{R} \alpha_{ir}^{\frac{1}{\sigma}} c_{ir}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \\
\text{s.t. } M &= \sum_{i=1}^{N} \sum_{r=1}^{R} p_{ir} c_{ir}
\end{aligned}
\tag{1}
$$

where $\sigma > 0$ is the elasticity of substitution and α_{ir} represents the consumer's taste for region-specific goods and services.[1]

From the consumer's utility maximization problem in Equation (1), I derive the consumer's demand for final goods from the first-order conditions.

$$
c_{ir} = \alpha_{ir} \left(\frac{p_{ir}}{P_C} \right)^{-\sigma} \frac{M}{P_C} \tag{2}
$$

P_C represents the consumer price index, which I set as the numeraire, (Blackburn and Moreno-Cruz, 2021; Lemoine, 2020).

$$
P_C = \left(\sum_{i=1}^{N} \sum_{r=1}^{R} \alpha_{ir} p_{ir}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} = 1
$$

2.1.2 Producers

Producers combine labor inputs and intermediate inputs according to a constant returns-to-scale CES production technology.[2]. The production technology for the producer in industry i and region r is given as

$$
y_{ir} = \left[\gamma_{ir}^{\frac{1}{\sigma}} (A_{ir}(W_r) L_{ir})^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{N} \sum_{s=1}^{R} \omega_{js,ir}^{\frac{1}{\sigma}} x_{js,ir}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{3}
$$

σ is the elasticity of substitution. γ_{ir} is the labor share parameter, $A_{ir}(W_r)$ is labor productivity as a function of local weather, and L_{ir} is labor input. $\omega_{js,ir}$ is the share parameter for intermediate inputs from a producer in industry j and region s, and $x_{js,ir}$ is the corresponding quantity of intermediate inputs.[3]

[1] Note, the elasticity of substitution parameter σ is the same for both the consumer's preferences and producers' technologies. Follows Baqaee (2018) and Blackburn and Moreno-Cruz (2021), this assumption allows a tractable closed-form solution. In reality, this elasticity parameter may differ between the consumer and the producers, so I consider a range of elasticity parameters in my emprical analysis below.

[2] The assumption that producers within an industry but located in different regions produce distinct goods or services is a common trade model assumption following Armington (1969).

[3] Note, we assume labor is the only primary factor of production and assume that weather shocks are factor-augmenting productivity shocks. We focus on labor for consistency with our empirical analysis below, but the model can be expanded to include other primary factor inputs without loss of generality, eg. Blackburn and Moreno-Cruz (2021). Similarly, one can generalize the results of this model for Hicks-neutral

Given their production technology, wages, and the prices of intermediate inputs, producers choose bundles of labor and intermediate inputs to minimize total costs. I consider both the scenario of no labor reallocation and free labor reallocation. When labor reallocation is constrained, a producer in industry i and region r faces wage rates w_{ir}. When labor is free to reallocate across the economy, producers face a single economy-wide wage rate $w_{ir} = w$. Prices of intermediate inputs are given as p_{ir}. The cost minimization problem for each producer in industry i and region r is given as

$$\begin{aligned} &\min_{L_{ir}, x_{jsir}} wL_{ir} + \sum_{j=1}^{N}\sum_{s=1}^{R} p_{js}x_{js,ir} \\ &\text{s.t. } y_{ir} = \left[\gamma_{ir}^{\frac{1}{\sigma}}(A_{ir}(W_r)L_{ir})^{\frac{\sigma-1}{\sigma}} + \sum_{j=1}^{N}\sum_{s=1}^{R}\omega_{jsir}^{\frac{1}{\sigma}}x_{js,ir}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{4}$$

From the first-order conditions for the cost minimization problems given by Equation (4), I derive the conditional intermediate input and labor demand.

$$x_{js,ir} = \omega_{jsir}\left(\frac{p_{js}}{\mu_{ir}}\right)^{-\sigma} y_{ir} \tag{5}$$

$$L_{ir} = \frac{\gamma_{ir}}{A_{ir}(W_r)^{1-\sigma}}\left(\frac{w_{ir}}{\mu_{ir}}\right)^{-\sigma} y_{ir} \tag{6}$$

Here μ_{ir} is the marginal cost of the good produced by industry i in region r, which is given as

$$\mu_{ir} = \left[\frac{\gamma_{ir}}{A_{ir}(W_r)^{1-\sigma}}w^{1-\sigma} + \sum_{j=1}^{N}\sum_{s=1}^{R}\omega_{js,ir}p_{js}^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{7}$$

3 General Equilibrium and Aggregate Impacts

3.1 Equilibrium

The general equilibrium of the competitive economy is a collection of prices, quantities, labor, and wages such that the following four conditions are satisfied:

1. **(Perfect Competition)** Markets are perfectly competitive, so equilibrium prices equal marginal costs, $p_{ir} = \mu_{ir}\ \forall i \in \{1, ..., N\}, r \in \{1, ..., R\}$.

productivity shocks. Baqaee and Farhi (2019) conceptualize this as a Hicks-neutral productivity shock to an intermediate producer that only supplies labor. Hicks-neutral productivity shocks give an additional amplification effect measured by the ratio of gross output relative to GDP.

2. **(Utility Maximization)** The representative consumer chooses consumption c_{ir} to solve the budget constrained utility maximization problem in Equation (1) given equilibrium prices p_{ir}.

3. **(Cost Minimization)** Representative producers choose factor demands L_{ir} and $x_{js,ir}$ to solve the cost minimization problem in Equation (4) subject to their production technology given equilibrium prices p_{ir} and wages w_{ir}.

4. **(Market Clearing)** Markets for output of each region-sector pair and the labor market clear. Output market clearing gives $y_{ir} = c_{ir} + \sum_{j=1}^{N}\sum_{s=1}^{R} x_{ir,js}$. When there is no labor reallocation, the labor market clearing condition is $\bar{L}_{ir} = L_{ir}\ \forall i \in \{1,...,N\}, r \in \{1,...,R\}$. When there is free labor reallocation, the labor market clearing condition is $\bar{L} = \sum_{i=1}^{N}\sum_{r=1}^{R} L_{ir}$.[4]

Before providing a closed-form solution for the general equilibrium of the economy, I first introduce a useful economic measure called the Leontief Inverse matrix. In matrix form, it is denoted as

$$\boldsymbol{\mathcal{L}} = [\mathbf{I} - \mathbf{\Omega}]^{-1} \tag{8}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{\Omega}$, known as the direct requirements matrix, is a matrix composed of the intermediate input share parameters $\omega_{js,ir}$. Elements $\mathcal{L}_{js,ir}$ of the Leontief Inverse measure the quantity of intermediate inputs required, both directly and indirectly, from each producer j in region s for producer i in region r to produce a unit of output.

I also define a productivity adjusted labor share parameter as $\gamma^*_{ir}(W_r) = \gamma_{ir}A_{ir}(W_r)^{\sigma-1}$. Scaling the labor share term by productivity, the adjusted labor share parameter measures effective labor share in production rather than the physical units of labor input. Because labor productivity is a function of a producer's local weather, so is their effective labor share.

Proposition 1. Economy Equilibrium *Applying the four conditions of a general equilibrium, I characterize a closed-form solution of the equilibrium prices, sales, and wages as follows.*

1. *Equilibrium prices of output*[5]

$$\mathbf{P}^{1-\sigma} = \boldsymbol{\mathcal{L}}'(\boldsymbol{\gamma}^*(\mathbf{W}) \odot \mathbf{w}^{1-\sigma}) \tag{9}$$

[4]Throughout I use *free labor reallocation* and *no labor reallocation* as extreme cases of costless labor reallocation across regions and industries and infinitely costly labor reallocation, respectively.

[5]The exponents here signify element-wise exponentiation. The symbol $\odot$ signifies the Hadamard product or element-wise multiplication of the vectors.

2. *Equilibrium sales*

$$\mathbf{P}^{\sigma} \odot \mathbf{Y} = \boldsymbol{\mathcal{L}}\boldsymbol{\alpha} M \tag{10}$$

3. *Equilibrium wages*

$$w_{ir} = \begin{cases} \left((\boldsymbol{\mathcal{L}}\boldsymbol{\alpha})' \boldsymbol{\gamma}^{*}(\mathbf{W}) \right)^{\frac{1}{\sigma-1}}, & \text{if free labor reallocation} \\ \left(\gamma^{*}_{ir}(W_r) L_{ir}^{-1} p_{ir}^{\sigma} y_{ir} \right)^{\frac{1}{\sigma}}, & \text{if no labor reallocation} \end{cases} \tag{11}$$

Equilibrium prices in Equation (9) relate the prices of output to their net consumption of factor demand, labor in this case, times factor prices, here wages. The net consumption of labor input accounts for both direct and indirect use of labor input embedded in intermediate inputs to production. This relationship highlights the role of input-output networks and substitutability in equilibrium outcomes. When goods are substitutes, $\sigma > 1$, producers that are more central in the input-output network have lower prices. Here, a more central producer is a larger net consumer of factor inputs. Alternatively, when goods are complements, $\sigma < 1$, producers that are more central in the input-output network have higher prices. Consider a shock to wages. When goods are complements, producers that are more central in the network are more exposed to that shock because its effect amplifies as it passes through the input-output network. Alternatively, if goods are substitutes, producers that are more central in the network are less exposed to the shock because its effect dampens as it passes through the input-output network.

Similarly, Equation (10) relates sales to total income in the economy and consumption shares of output, both direct and indirect. This relationship indicates that producers that more central in the input-output network–here central in that they are larger net suppliers of output–will have higher sales. This follows intuitively. If a producer is an important supplier, both directly through final sales to the consumer and indirectly through supplying intermediate inputs to other producers, they receive a larger share of the total income in the economy.

Finally, Equation (11) relates wages to labor demand, both with free labor reallocation and with no labor reallocation. When there is free labor reallocation, there is a single economy-wide wage rate. When there is no labor reallocation, each producer representing an industry in a region faces a distinct wage rate. As with the price of output, wages depend on the net demand for labor and the elasticity of substitution parameter.

Though the direct effects of weather were defined to be strictly local, a quick glance at these equilibrium characterizations indicates that these direct effects can propagate through the input-output networks in the economy, creating far-reaching impacts. Let's consider this in more detail.

3.2 Comparative Statics

Given the closed-form characterization of the equilibrium, how do weather shocks impact equilibrium prices and quantities? Let's consider an idiosyncratic weather shock to a producer in industry i and region r in a comparative statics analysis. Assume there is no direct effect from the weather shock for any other producers to clarify underlying mechanisms. I separately consider the net effect for the producer in industry i and region r, which I term the *own effect*, and the net effect for other producers in industries j across regions s, which I term the *indirect effect*. I also separately consider the scenarios of free labor reallocation and no labor reallocation.

Proposition 2. Comparative Statics (Own Effects) *The quasi-elasticities of wages, labor input, and sales for a producer in industry i and region r with respect to an idiosyncratic weather shock are given as*

1. *Sales effect*
$$\frac{\partial \log(p_{ir}^{\sigma} y_{ir})}{\partial W_r} = \lambda_{ir} \frac{\partial \log(A_{ir}(W_r))}{\partial W_r} \tag{12}$$

2. *Wage effect*
$$\frac{\partial \log(w_{ir})}{\partial W_r} = \begin{cases} \lambda_{ir} \frac{\partial \log(A_{ir}(W_r))}{\partial W_r}, & \text{if free labor reallocation} \\ \left(\frac{(\sigma-1)}{\sigma} + \frac{\lambda_{ir}}{\sigma}\right) \frac{\partial \log(A_{ir}(W_r))}{\partial W_r}, & \text{if no labor reallocation} \end{cases} \tag{13}$$

3. *Labor effect*
$$\frac{\partial \log(L_{ir})}{\partial W_r} = \begin{cases} (\sigma - 1)(1 - \lambda_{ir}) \frac{\partial \log(A_{ir}(W_r))}{\partial W_r}, & \text{if free labor reallocation} \\ 0, & \text{if no labor reallocation} \end{cases} \tag{14}$$

where $\lambda_{ir} = \frac{w_{ir} L_{ir}}{\sum_j \sum_s w_{js} L_{js}}$ is the share of value-added for producer i in region r relative to the GDP of the economy.

The *Own Sales Effect* is the marginal change in sales for a producer due to a weather shock to that producer. Weather does not affect the underlying production network structure, captured by the Leontief-Inverse matrix $\boldsymbol{\mathcal{L}}$ or on consumer's tastes $\boldsymbol{\alpha}$. Thus, from Equation 10, weather can only affect sales through changes to aggregate income. Independent of assumptions about labor reallocation, this aggregate income effect is always given as the size of the shocked producer times their sensitivity to the weather shock.

The *Own Wage Effect* captures how the wage rate faced by the producer responds to a weather shock to that producer. When there is no labor reallocation, this effect is the same for all producers because there is a single wage rate. In this case, the *Own Wage Effect* is the same as the *Own Sales Effect* and captures the change in income from the change in productivity for the affected sector. When there is no labor reallocation, the *Own Wage Effect* also depends on the elasticity of substitution.

The *Own Labor Effect* only exists when labor is allowed to reallocate. It captures how a producer's labor input responds to a weather shock to that producer. The sign and magnitude of this effect depends on the economic size of the producer and the elasticity of substitution. When goods are substitutes ($\sigma > 1$), labor input increases for a positive weather shock, as consumption substitutes towards the more relatively productive producer. When goods are complements ($\sigma < 1$), labor reallocates away from the producer to increase complementary production.

Now let's consider the *indirect effects*. These effects capture the change in equilibrium prices and quantities for producers that are not *directly* affected by the idiosyncratic weather shock.

Proposition 3. Comparative Statics (Indirect Effects) *The quasi-elasticities of wages, labor input, and sales for a producer in industry j and region s with respect to an idiosyncratic weather shock to a producer in industry i and region r where $i, r \neq j, s$ are given as*

1. *Sales effect*
$$\frac{\partial \log(p_{js}^{\sigma} y_{js})}{\partial W_r} = \lambda_{ir} \frac{\partial \log(A_{ir}(W_r))}{\partial W_r} \tag{15}$$

2. *Wage effect*
$$\frac{\partial \log(w_{js})}{\partial W_r} = \begin{cases} \lambda_{ir} \frac{\partial \log(A_{ir}(W_r))}{\partial W_r}, & \text{if free labor reallocation} \\ \frac{\lambda_{ir}}{\sigma} \frac{\partial \log(A_{ir}(W_r))}{\partial W_r}, & \text{if no labor reallocation} \end{cases} \tag{16}$$

3. *Labor effect*
$$\frac{\partial \log(L_{js})}{\partial W_r} = \begin{cases} -\lambda_{ir}(\sigma - 1) \frac{\partial \log(A_{ir}(W_r))}{\partial W_r}, & \text{if free labor reallocation} \\ 0, & \text{if no labor reallocation} \end{cases} \tag{17}$$

The *Indirect Sales Effect* and the *Indirect Wage Effect* with no labor reallocation are identical to the *Own Effect* counterparts. This is because both effects reduce to an income effect, which holds independent of the producer when there is one wage rate. Alternatively, when labor is free to reallocate, the *Indirect Wage Effect* again depends on the size of the producer directly affected by the idiosyncratic weather shock and the elasticity of substitution. When goods are substitutes, $\sigma > 1$, the *Indirect Wage Effect* is smaller without labor reallocation. When goods are complements, $\sigma < 1$, the *Indirect Wage Effect* is larger without reallocation.

The *Indirect Labor Effect* characterizes the change in labor inputs for a producer not directly affected by the weather shock. The sign and magnitude of this effect depends on the size of the producer and the elasticity of substitution. When goods are substitutes ($\sigma > 1$), labor input decreases for a positive weather shock as consumption substitutes towards the relatively more productive producer. When goods are complements ($\sigma < 1$), a positive weather shock to producer i in region r leads to labor reallocation towards producer j in region s to increase complementary production.

The existence of these indirect effects provides an important insight for econometric estimates of climate impacts and the projection of regional climate impacts. Specifically, Proposition 3 indicates that local weather shocks can have indirect spillover effects on other producers in an economy. Without this theoretical underpinning, previous reduced-form empirical studies provide evidence supporting the economic importance of this finding. For example, Jones and Olken (2010) find empirical evidence that higher temperatures negatively impact the growth of trade exports in poorer countries. With firm-level data, Boehm et al. (2018) find empirical evidence that the Tohoku Earthquake in 2011 negatively impacted Japanese firms and that these shocks propagated to negatively impact firms that relied on imported inputs from these Japanese firms. This result indicates that econometric analyses that use economic outcomes, such as GDP, as the dependent variable but do not control for these potential spillover channels may result in biased estimates. This bias can be corrected for by either explicitly incorporating spillover channels in the estimating equation or by focusing on economic primitives, such as productivity, rather than equilibrium outcomes. I do the latter in the empirical analysis below. Additionally, when applying empirical estimates to project or estimate the regional impacts of climate, one needs to account for propagation through these spillover channels.

3.3 Aggregate Impacts

Equipped with an equilibrium solution and comparative statics for weather shock impacts, let's now turn to how local weather shocks aggregate to generate macroeconomic impacts in equilibrium. Let $\mathcal{Y}$ be the aggregate output of the economy. Again consider an idiosyncratic weather shock to a producer in industry i and region r, assuming no direct affect to other producers in the economy. I first characterize the impact of this weather shock on aggregate output to a first-order approximation.

Proposition 4. First-order aggregate impact of idiosyncratic weather shock *To a first-order, the aggregate impact of a weather shock directly to a producer in industry i and region r is given by*

$$\frac{\mathrm{d}\log\mathcal{Y}}{\mathrm{d}W_r} = \lambda_{ir}\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r} \tag{18}$$

To a first-order, the aggregate impact of a weather shock directly to a producer in industry i and region r is governed by two factors. The first is the economic size of the producer subjected to the weather shock, given as the ratio of their value-added to the GDP of the economy. The second is the marginal effect of the weather shock on the producer's labor productivity. For a given shock to productivity, a larger producer will have a larger impact on the aggregate output of the economy. And, for a given producer size, a producer that is more sensitive to weather shocks will have a larger impact on aggregate output. This result is consistent with Hulten's Theorem (Hulten, 1978) and holds for any factor augmenting productivity shock in a competitive economy, independent of production technology (Baqaee and Farhi, 2019).

The intuition behind this result is as follows. The aggregate output of the economy is equal to the aggregate income of the economy, which in this model only comes from the labor supplied times the corresponding wage rates. Labor is inelastically supplied, so there is no change in the total quantity of labor across the economy. Thus, the impact of an idiosyncratic weather shock on aggregate output, to a first-order, only comes from the aggregate effect on wages, as captured in Equation (13). This result is independent of the ability of labor to reallocate.

Equation (18) characterizes the aggregation equation typical used in empirically-based projections of climate impacts. For example, to project climate change damages in terms of gross world product, Burke et al. (2015) and Burke et al. (2018) aggregate country-level climate damages weighted by their share of gross world product. When production is log-linear, i.e. Cobb-Douglas, Proposition 4 exactly holds. But, for non-linear production technologies, production networks introduce non-linearities in aggregate impacts (Baqaee and Farhi, 2019). I characterize these non-linearities by considering the second-order terms in an approximation of the aggregate impact weather shocks. First, again consider an idiosyncratic weather shock that only directly affects a producer in industry i and region r.

Proposition 5. Second-order aggregate impact of an idiosyncratic weather shock. *The second-order aggregate impact of a weather shock directly to producer i in region r is* *given by*

$$\frac{\mathrm{d}^2 \log \mathcal{Y}}{\mathrm{d}W_r^2} = \frac{\mathrm{d}\lambda_{ir}}{\mathrm{d}W_r}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r} + \lambda_{ir}\frac{\mathrm{d}^2\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r^2}$$
$$= \begin{cases} \lambda_{ir}(1-\lambda_{ir})(\sigma-1)\left(\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r}\right)^2 + \lambda_{ir}\frac{\mathrm{d}^2\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r^2}, & \text{if free labor reallocation} \\ \lambda_{ir}(1-\lambda_{ir})(1-\frac{1}{\sigma})\left(\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r}\right)^2 + \lambda_{ir}\frac{\mathrm{d}^2\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r^2}, & \text{if no labor reallocation} \end{cases} \tag{19}$$

The second-order term for the aggregate impact of an idiosyncratic weather shock to a producer in industry i and region r is composed of two components. The first component, given by the first term on the right-hand side of Equation (19), captures economic production non-linearities. When a weather shock impacts the producer's productivity, it changes the value-added share of the producer. In turn, this changes the aggregate impact of the weather shock.[6] The second component, given by the second term on the right-hand side of Equation (19), captures non-linearities in the marginal effect of the weather shock on productivity. When the marginal effect of a weather shock is constant, this term is zero. However, considerable empirical evidence, including in the empirical analysis below, suggests that weather shock impacts exhibit strong non-linearities.

I further break down the first term on the right-hand side of Equation (19), which captures economic production non-linearities. This non-linearity is characterized by the value-added share of the affected producer, the elasticity of substitution, and the marginal effect of the weather shock on labor productivity. The value-added share, λ_{ir}, is always less than one, so the sign of this second-order term depends on the elasticity of substitution. I illustrate this dependence in Figure 1.

When $\sigma = 1$, i.e. Cobb-Douglas production technology, value-added shares in the economy are constant, and this term is equal to zero. As a result, aggregate output is linear in the size of the resulting productivity shock. When goods are substitutes, $\sigma > 1$, this term is positive. Thus, the aggregate impact of a weather shock is convex in the size of the resulting productivity shock. When goods are substitutes, intermediate inputs are reallocated and sourced from more productive producers. Thus, for a positive productivity shock, there will be a substitution towards the affected producer. This amplifies the aggregate

[6] With continuous observations of weather and economic production one could integrate the impacts of weather shocks over time (See footnote 45 of Baqaee and Farhi (2019) for more on this). This would negate the need for these higher-order terms beyond eliciting economic intuition. However, even if weather data can be gathered at the temporal resolution of days or even hours, economic data is typically measured in years or, at best, months. Thus, we use this approximation approach to empirically estimate weather shock impacts in the empirical analysis below.

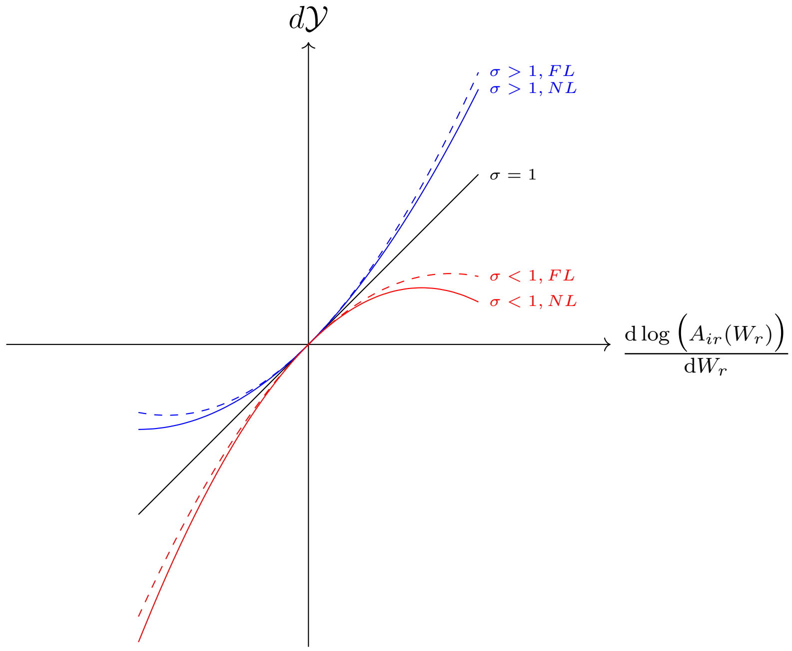


Figure 1: Aggregate effect of idiosyncratic shock for different elasticities of substitution and labor reallocation assumptions. FL indicates free labor reallocation. NL indicates no labor reallocation

impact of their positive productivity shock. For a negative productivity shock, there will be substitution away from the affected producer. This dampens the aggregate impact of their negative productivity shock. The same intuition holds for labor reallocation. When labor is free to reallocate, this increases the convexity. Given a positive productivity shock, the affected producer can increase their labor input. This further amplifies their aggregate impact. The opposite holds for a negative productivity shock. Alternatively, when goods are complements, $\sigma < 1$ the term is negative. Thus, the aggregate impact of a weather shock is concave in the size of the resulting productivity shock. The aggregate impact of a positive productivity shock will be dampened and a negative productivity shock will be amplified. The ability of labor to freely reallocate moderates this concavity.

A second-order approximation of the aggregate impact of weather shock also includes the interaction of weather shocks to producers throughout the economy in cross-effect terms. Consider the cross-effect of simultaneous shocks that directly affect a producer in industry i and region r and another distinct producer in industry j and region s.

Proposition 6. Second-order effect of correlated shocks. *The second-order aggregate impact of simultaneous weather shocks to a producer in industry i and region r and a producer* *in industry j and region s where $i, r \neq j, s$ is given by*

$$\begin{aligned}\frac{\mathrm{d}^2 \log \mathcal{Y}}{\mathrm{d}W_r \mathrm{d}W_s} &= \frac{\mathrm{d}\lambda_{ir}}{\mathrm{d}W_s} \frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r} + \lambda_{ir} \frac{\mathrm{d}^2 \log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r \mathrm{d}W_s} \\ &= \begin{cases} -\lambda_{ir}\lambda_{js}(\sigma - 1) \frac{\mathrm{d}\log\big(A_{js}(W_s)\big)}{\mathrm{d}W_s} \frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}, & \text{if free labor reallocation} \\ -\lambda_{ir}\lambda_{js}(1 - \frac{1}{\sigma}) \frac{\mathrm{d}\log\big(A_{js}(W_s)\big)}{\mathrm{d}W_s} \frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}, & \text{if no labor reallocation} \end{cases}\end{aligned} \tag{20}$$

The second-order term for the aggregate impact of simultaneous weather shocks is again composed of two components. The first component, given by the first term on the right-hand side of Equation (20), captures economic production non-linearities. When a producer in industry i and region r experiences a weather shock that changes their productivity, it affects their value-added share and the value-added share of each other producer. Thus, a weather shock to a producer in industry i and region r will, in turn, affect the aggregate impact of simultaneous shock to a different producer in industry j and region s. The second component, given by the second term on the right-hand side of Equation (20), captures non-linearities in the marginal effect of weather shocks. This latter component is zero because, by definition, weather shocks are local to the producers.

I further break down the first term on the right-hand side of Equation (20), which captures economic production non-linearities. This non-linearity is characterized by the value-added shares of both producers, the elasticity of substitution, and the marginal effect of weather shocks to both producers. When production is log-linear, $\sigma = 1$, this cross-term is zero because value-added shares are constant. When goods are substitutes, $\sigma > 1$, this cross-term is negative. A weather shock that positively affects the productivity of a producer in industry i and region r causes substitution away from other producers in industries j across regions s. This dampens the aggregate impact of weather shocks to those other producers. When labor is free to reallocate, the aggregate impact of weather shocks to those other producers is dampened even further. When goods are complements, $\sigma < 1$, this cross-term is positive. A weather shock that positively affects the productivity of a producer in industry i and region r amplifies the aggregate impact of weather shocks to other producers in industries j across regions s. When labor is free to reallocate, the aggregate impact of weather shocks to those other producers is amplified even further.

These second-order terms highlight the role of non-linearities in production and weather shocks in generating non-linearities in aggregate impacts. But heterogeneity in the effect of weather shocks across the economy is also critical to these non-linearities. To see this, let's compare the first term on the right-hand side of Proposition 5 and the first term on the right-hand side of Proposition 6.

Corollary 1. Heterogeneity and non-linearities in aggregate impacts. *When all the producers in an economy experience an identical change in productivity from weather shocks, such that* $\frac{d\log\left(A_{ir}(W_r)\right)}{dW_r} = \frac{d\log\left(A_{js}(W_s)\right)}{dW_s}$ $\forall i,j \in \{1,...,N\}$ *and* $\forall r,s \in \{1,...,R\}$*, the sum of the second-order aggregate impacts of weather shocks reduces to sum of non-linearities in the marginal effects of the weather shocks.*

From Corollary 1, non-linearities in aggregate impacts due to non-linearities in economic production only exist when there is variation in the marginal effect of weather shocks on producers' productivity throughout the economy. These non-linearities, represented by the first term on the right-hand side of Equations (19) and (20) come from changes in value-added shares. When all producers in the economy experience an identical change in productivity, value-added shares remain constant. So, without heterogeneity, these non-linearities vanish. All that remains are non-linearities in the marginal effects of weather shocks.

Corollary 2. Heterogeneity and labor reallocation. *When all the producers in an economy experience an identical change in productivity from weather shocks, such that* $\frac{d\log\left(A_{ir}(W_r)\right)}{dW_r} = \frac{d\log\left(A_{js}(W_s)\right)}{dW_s}$ $\forall i,j \in \{1,...,N\}$ *and* $\forall r,s \in \{1,...,R\}$*, the ability of labor to reallocate has no effect on aggregate impacts.*

Heterogeneity is similarly critical for the effect on labor reallocation on aggregate impacts of weather shocks across the economy. When weather shocks have a homogeneous effect on producers' productivity throughout the economy, there is no reallocation of factor inputs. Labor inputs remain constant.

Corollaries 1 and 2 show that heterogeneity in weather shocks at a local level can matter for the aggregate impact of these weather shocks. Empirical studies that ignore this heterogeneity may over- or under-estimate the aggregate impacts of weather shocks or climate. While this heterogeneity matters in theory, does it matter in practice? In the following sections, I turn to an empirical setting to empirically constrain the economic importance of accounting for variability in the local effect of weather shocks.

Combining the first-order and second-order terms, I characterize the aggregate impact of micro-level weather shocks throughout an economy as,[7]

$$\Delta \log \mathcal{Y} = \sum_{i,r} \frac{\mathrm{d} \log \mathcal{Y}}{\mathrm{d}W_r} \Delta W_r + \sum_{i,r} \frac{1}{2} \frac{\mathrm{d}^2 \log \mathcal{Y}}{\mathrm{d}W_r^2} \Delta W_r^2 + \sum_{i,r} \sum_{j,s \neq i,r} \frac{1}{2} \frac{\mathrm{d}^2 \log \mathcal{Y}}{\mathrm{d}W_r \mathrm{d}W_s} \Delta W_r \Delta W_s \tag{21}$$

[7]Here I use $\sum\limits_{i,r}$ and $\sum\limits_{j,s}$ as a short hands for the joint summations $\sum\limits_{i=1}^{N}\sum\limits_{r=1}^{R}$ and $\sum\limits_{j=1}^{N}\sum\limits_{s=1}^{R}$, respectively.

Equation (21) provides a tractable approach to linking the microeconomic impacts of weather shocks in an economy and their aggregate macroeconomic impact. Specifically, estimating this equation requires the following: a measure of the economic size of producers, represented by their value-added share in the economy, a characterization of the response of labor productivity to weather shocks, and data on the size of weather shocks. The first and third can be observed and measured with available data. While the second cannot be directly observed, it can be empirically estimated with econometric methods.

4 Empirical Context

Equipped with the theoretical findings of the previous section, I now turn to an empirical setting in the United States. In this section, I describe the data and empirically estimate the relationship between labor productivity and weather shocks at the finest resolution possible with publicly available data following insights from the previous section. In the next section, I apply the theoretical findings of the previous section to construct estimates of the aggregate impacts of weather shocks across the US economy according to Equation (21). I use these estimates to explore the economic importance of accounting for variability in weather and non-linearities in economic production.

4.1 Data

Estimating the macroeconomic impact of micro-level weather shocks requires the following: a measure of the economic size of producers, represented by their value-added share in the economy, a characterization of the response of labor productivity to weather shocks, and data on the size of weather shocks.

4.1.1 Economic Data

Economic data for my empirical analysis comes from publicly available data provided by the Bureau of Economic Analysis (BEA). I gather economic data for 14 2-digit NAICS industry classifications across all 3,080 counties in the contiguous United States from 2001 to 2017.[8] The BEA censors select observations at this resolution to mitigate concerns about identification and privacy. Censored observations are predominantly small county-industry pairs, and the total economic size of censored observations comprises only around 2% of

[8]Data was retrieved from https://apps.bea.gov/regional/downloadzip.cfm. I drop the government sector because it is not a profit-maximizing sector, and thus is inconsistent my theoretical model. There is empirical evidence that weather and climate shocks, such as hurricanes, can exert budgetary pressure on local governments, particularly in minority communities Jerch et al. (2020).

aggregate GDP in any given year. Thus, dropping these censored observations will not change the estimate of aggregate impacts by much. Also, data is likely censored on economic size, e.g. value-added, so there is little concern for selection bias in empirical estimates of the effect of weather shocks on labor productivity growth.

For the analysis, I measure the value-added share of industry-county pairs using data on real GDP in chained 2012 US dollars. Figure 2**(a)** displays the largest industry classification for each county in 2001, measured by value-added. This figure highlights the heterogeneity in industrial composition across counties. There are no publicly available data on labor productivity or labor productivity growth at the county-by-industry resolution. Thus, I use publicly available data from the BEA to construct a measure of labor productivity growth at this resolution. Details of how I construct this measure are in Appendix B. When constructing this labor productivity growth measure, and in the analyses below, I assume an elasticity of substitution of $\sigma = 0.5$. This assumption follows empirical evidence from Atalay (2017) and Boehm et al. (2018). In Appendix C, I present empirical results for alternative values for the elasticity of substitution. Appendix B also provides more descriptive statistics for the economic data.

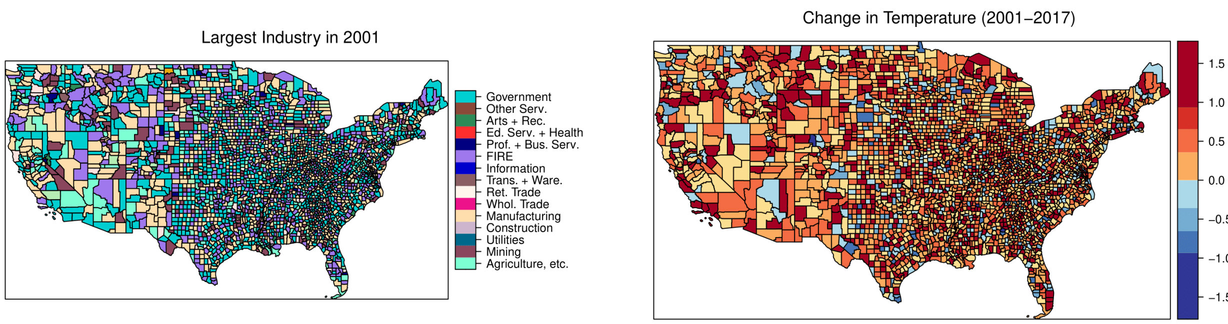
4.1.2 Weather Data

Following previous empirical studies, I capture weather using measures of surface temperature and precipitation. I measure these using data from Schlenker (2020)[9] and is based on the PRISM climate dataset. The data consists of gridded minimum and maximum temperature and cumulative precipitation at a 2.5 mile by 2.5 mile spatial resolution. The gridded dataset is constructed by interpolating weather station observation data. Weather station observation data often contain missing observations. These missing observations can bias econometric estimates if there is a correlation between the reason for missing data, such as financial constraints or political events, and the outcomes of interest (Auffhammer et al., 2013). To mitigate concerns of bias from missing station data, the gridded dataset is constructed using a constant set of stations over the time horizon.

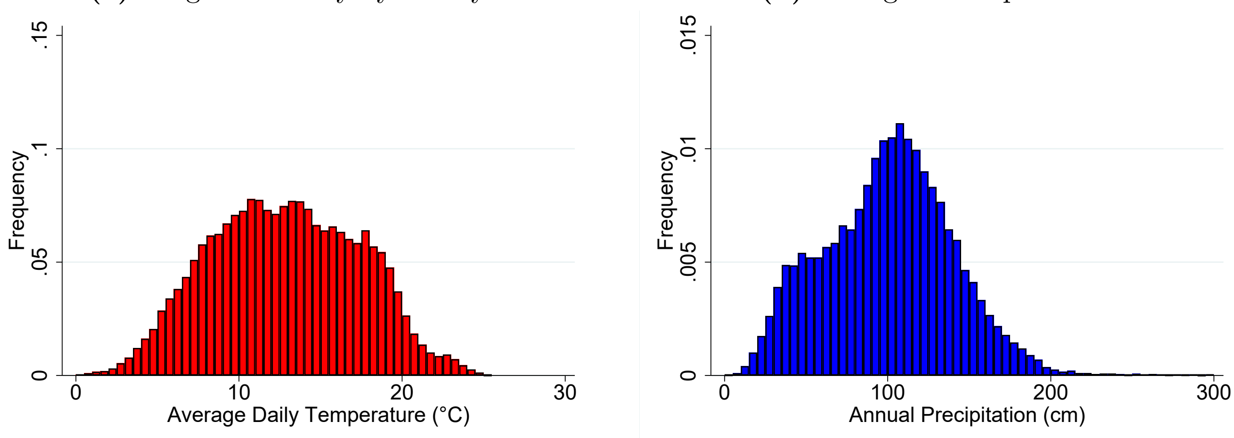
To match the weather data with the economic data, I construct annual measures of temperature and precipitation at the county level. I first calculate polynomials of daily temperature and daily precipitation at the grid-cell level. Daily temperature is the simple mean of daily maximum and daily minimum temperature, and daily precipitation is cumulative precipitation. I calculate polynomials at the grid-cell level to avoid averaging out extremes. These polynomials are then spatially aggregated to the county level by taking the population-weighted mean across grid-cells within counties. Population weights are population density

[9]Data is publicly available at http://www.columbia.edu/ ws2162/links.html

in 2000 using data from the Gridded Population of the World, v3 (Center for International Earth Science Information Network, 2005). Finally, I sum the county level polynomials of daily temperature and precipitation for each year.



(a) Largest industry by county. **(b)** Change in temperature.



(c) Distribution of temperature observations. **(d)** Distribution of precipitation observations.

Figure 2: Descriptive Statistics. The largest industry for each county is defined as the industry with the largest value-added share in the county. Change in average temperature in Panel **(b)** is defined in the difference between annual average daily temperature in 2017 and annual average daily temperature in 2001. Average temperature in Panel **(c)** is defined as annual average daily temperatures. Precipitation in Panel **(d)** is defined as cumulative annual precipitation.

Panels **(c)** and **(d)** of Figure 2 display the distribution of annual average daily temperature and annual precipitation observations across the sample time period and across US counties. These are approximately normally distributed and highlight the variability of weather across both space and time. Figure 2**(b)** displays the change in annual average daily temperature for each county over the sample period. On average, temperature rises by about 0.1°C over the sample period, but Figure 2**(b)** again highlights the variation in temperature change across space. Appendix B provides additional descriptive statistics of the weather data.

4.2 Empirical Estimate of Microeconomic Response Functions

To estimate the aggregate impact of micro-level weather shocks, I need data on the relationship between weather shocks and labor productivity growth. Since this relationship cannot be directly observed, I use panel data fixed effects methods to empirically estimate the response function (Dell et al., 2014). Specifically, I consider the following estimating equation,

$$\Delta \log(A_{ict}) = f_i(\boldsymbol{T}_{ct}) + g_i(\boldsymbol{P}_{ct}) + \alpha_{ic} + \alpha_{st} + \epsilon_{ict} \tag{22}$$

where i denotes industry, c denotes county, s denotes state, and t denotes year. Thus, $\Delta \log(A_{ict})$ is the growth in labor productivity for industry i in county c in year t. We explain this growth as a function of a vector of temperature measures $\boldsymbol{T}_{ct}$ and a vector precipitation measures $\boldsymbol{P}_{ct}$ controlling for industry-by-county fixed effects α_{ic} and state-by-year fixed effects α_{st}. After controlling for these fixed effects, the identifying variation comes from variations in temperature and precipitation over time within counties. I cluster standard errors by state and industry to control for potential correlation in error structure.

The response functions $f_i(\boldsymbol{T}_{ct})$ and $g_i(\boldsymbol{P}_{ct})$ capture the relationship between labor productivity growth and temperature and precipitation. I denote these functions with the subscript i because they may vary across industries. To date, there has been no evidence favoring a specific functional form for this relationship, but there is considerable empirical evidence that this relationship is non-linear, eg. Schlenker and Roberts (2009) and Burke et al. (2015). Thus, I consider $\boldsymbol{T}_{ct}$ as a third-order polynomial of daily average temperatures and $\boldsymbol{P}_{ct}$ as a second-order polynomial of daily precipitation, each summed annually. $f_i(\boldsymbol{T}_{ct})$ and $g_i(\boldsymbol{P}_{ct})$ are then linear combinations of non-linear measures of temperature and precipitation. This permits the estimation of a linear regression model.

I first estimate a pooled response function across industries. This constrains all industries to have a uniform relationship between labor productivity and temperature and precipitation. Figure 3 plots the estimated relationship between temperature and labor productivity growth. Consistent with previous empirical estimates of the relationship between temperature and economic productivity or output, I find evidence of a non-linear inverted U-shaped relationship. I find a peak growth temperature of around 15°C, which is also consistent with previous evidence. This inverted U-shaped relationship indicates that for industries in colder counties, i.e. those with temperatures below 15°C, labor productivity growth increases when temperatures rise. For industries in warmer counties, i.e. those with temperatures above 15°C, labor productivity growth decreases when temperatures rise.

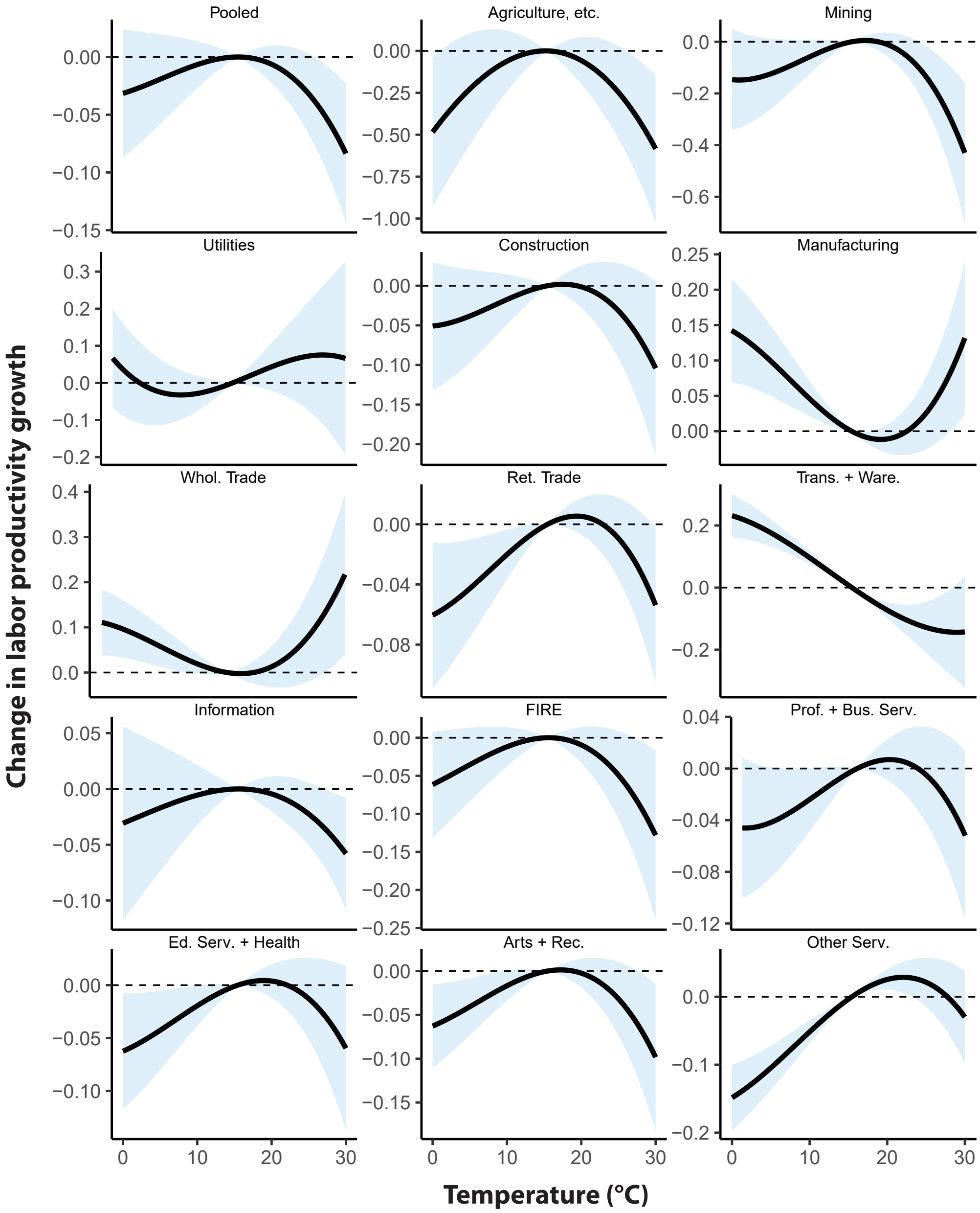


Figure 3: Microeconomic Temperature Response Functions. Empirically estimated marginal labor productivity growth-temperature response functions for pooled response and industry-specific response. Marginal effects plotted relative to the peak growth temperature in the pooled estimate, around 15°C. Lines represent mean estimates and blue fill represents 90% confidence interval using clustered standard errors.

Previous empirical estimates at higher levels of aggregation, such Dell et al. (2012) and Burke et al. (2015) at the country level, do not find evidence of a statistically significant effect of precipiation on economic outcomes. However, at a higher spatial resolution, I find that precipitation has a statistically significant affect on labor productivity growth. This is shown for the pooled response and for select industries in Figure 9 in Appendix C. Finding a statistically significant effect of precipitation at a higher spatial resolution is consistent with Damania et al. (2020). They show that spatial aggregation can wash out variation in precipitation that is important for identification and masks the impact of precipitation on economic growth. This provides another argument for conducting empirical analyses of climate impacts at a higher level of resolution.

Next, I relax the constraint that all industries have a uniform relationship between productivity growth and temperature and precipitation by allowing for distinct responses for each industry classification. I do this by interacting an industry classification dummy variable with the polynomials of temperature and precipitation. If the responses across industries are truly uniform, I should recover a similar relationship for each industry, which should also look like the pooled response function.

Figure 3 displays the estimated relationship between labor productivity growth and temperature for each industry classification. It is clear that the response is not uniform, rather there is substantial heterogeneity in response function across industries in both the shape of the response and the magnitude of the response. Most industries share the commonly documented inverted U-shape relationship but vary in the intensity of the marginal effect. However, I find that the relationship takes a completely different shape for some industries. For example, the relationship between temperature and growth for the Manufacturing and Wholesale Trade sectors form a U-shape, rather than an inverted U-shape. It is not obvious why the shapes take the different forms that they do. One could speculate, but a more detailed analysis to explain these relationships is beyond the scope of this paper and is left as an important area for future work.

5 Aggregate Impacts

I now have the data needed to estimate the aggregate economic impact of weather shocks across the US economy according to Equation 21. To explore the economic importance of the interaction of local weather variability and non-linearities in aggregation as exemplified in Corollary 1, I first approximate aggregate impacts to a first-order and then consider second-order terms.

5.1 First-order Impacts

Proposition 4 says that a first-order approximation of the aggregate impact of weather shocks is equal to the weighted sum of microeconomic impacts where the weights are the value-added shares of producers. I accordingly aggregate local weather shock impacts across county-industry pairs and sample years using the empirically estimated microeconomic response functions from Section 4. Growth impacts are converted into level impacts by multiplying by aggregate GDP in the previous period. This gives

$$\Delta \mathrm{GDP}_t = \mathrm{GDP}_{t-1} \sum_{i=1}^{N} \sum_{c=1}^{R} \lambda_{ict} \frac{\mathrm{d} \log A_{ic}(W_c)}{\mathrm{d} W_c} \Delta W_c \tag{23}$$

I measure a discrete analog of the impact of climate changes on labor productivity growth relative to 2001 using the estimates from Equation (22).

$$\frac{\mathrm{d} \log A_{ic}(W_c)}{\mathrm{d} W_c} \Delta W_c = (f_i(\boldsymbol{T}_{ct}) + g_i(\boldsymbol{P}_{ct})) - (f_i(\boldsymbol{T}_{c,2001}) + g_i(\boldsymbol{P}_{c,2001})) \tag{24}$$

Thus, my estimates capture the impacts of changes in weather relative to 2001, not the total level impacts of weather shocks.

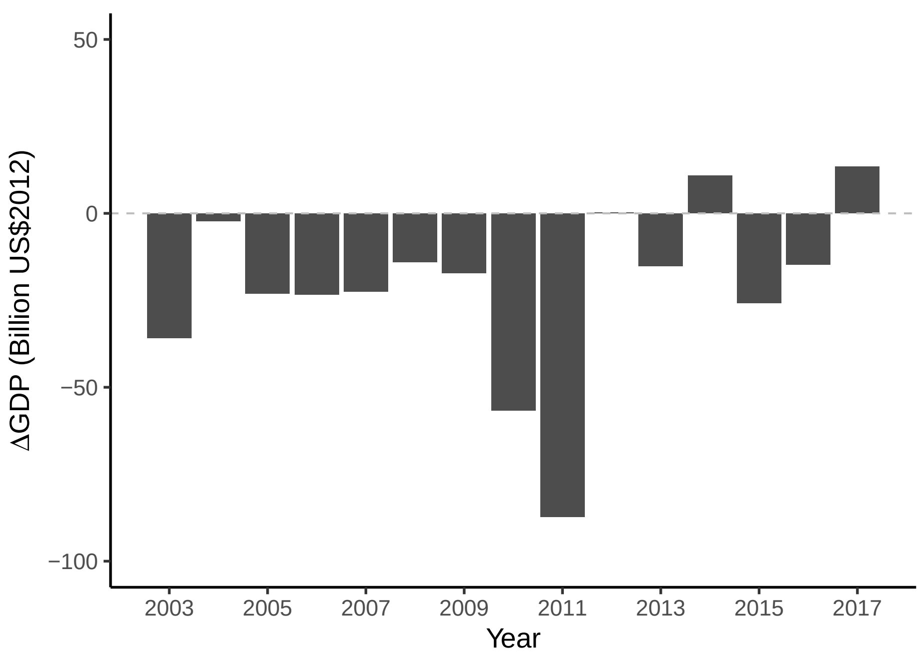


Figure 4: First-order Estimate of Aggregate Impacts. First-order approximation of the aggregate impacts of weather shocks across county-industry producers. Weather shocks are defined as changes in temperature and precipitation from their 2001 levels.

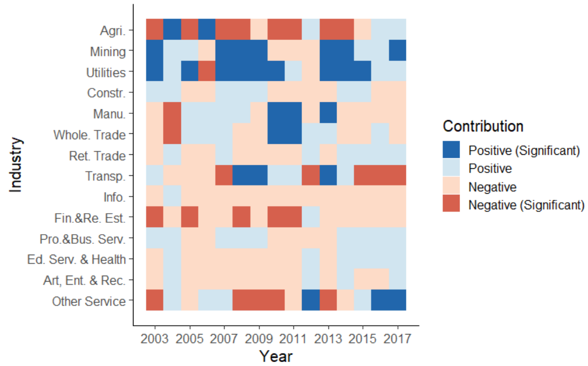
Figure (4) shows estimates of a first-order approximation of the macroeconomic impacts for each year from 2003 to 2017. The aggregate impacts are predominately negative but vary in sign and magnitude across the sample years. The largest absolute impact is an aggregate loss of around 0.5% of GDP in 2011. While aggregate impacts are negative in most years, I find that weather shocks increase aggregate output in the years 2012, 2014, and 2017. The cumulative macroeconomic impact over the sample period is an aggregate loss of $350 billion.

I deconstruct these first-order macroeconomic impact estimates into their underlying contributions across industries and space. Aggregate industry-level contributions are calculated as the aggregate productivity impacts across counties within each industry weighted by the value-added share of each county. Similarly, aggregate county-level contributions are calculated as the aggregate productivity impacts across industries within each county weighted by the value-added share of each industry. Finally, county-by-industry contributions are simply the value-added share weighted productivity impact for each respective county-industry pair. Note, these *contributions* reflect how productivity shocks at each scale impact the aggregate economy. They do not necessarily reflect the net outcome for the industry, county, or county-industry pair. To estimate the net outcomes for each industry, county, or county-industry pair, I would have to account for spillovers, as captured in Proposition 3.

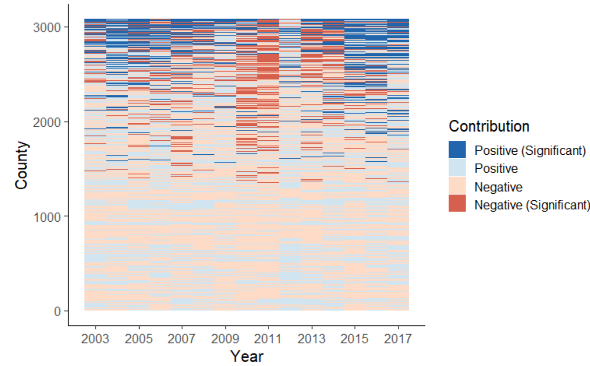
Figures 5(a) and (b) display contributions to the macroeconomic impacts in each year by industry and county, respectively. Counties are sorted by their frequency of statistically significant contributions. Figure 5(c) displays the contributions of county-industry pairs to aggregate impacts in the year 2012. I display estimates for 2012 because the estimated aggregate impacts in this year are the closest to zero of all the sample years. I show the results for other years in Appendix C. I calculate statistical significance of contributions to aggregate economic growth at the 95% confidence level using the variance-covariance matrix recovered from empirical estimates of the microeconomic response functions from Section 4.

Immediately clear is the considerable heterogeneity in contributions across both space and industry. Within a given year, there are positive and negative contributions from different counties and industries. And within a given county or industry, there is variation in their contributions to aggregate impacts across years. The former is due to heterogeneity in both weather shocks and response to weather shocks across industries and counties. The latter is solely due to heterogeneity in weather shocks over time since response functions are held constant.

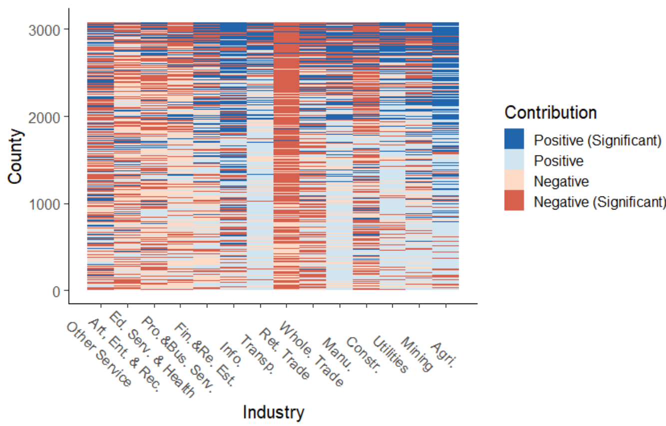
The heterogeneity in contributions and the frequency of statistically significant contributions grows with higher resolution. For example, consider impacts in the year 2012. I estimate that the aggregate impact of weather shocks in 2012 is relatively close to $0. Yet, Figure 5**(c)** shows that the microeconomic impacts are far from zero. The contributions from county-industries are highly varied, and many are statistically significant.



(a) Industry-level Contributions.



(b) County-level Contributions.



(c) County-Industry-level Contributions in 2012.

Figure 5: Contributions to First-Order Estimate of Aggregate Impacts. Decomposition of the underlying contributions to the first-order estimate of aggregate impacts of weather shocks. Weather shocks are defined as changes in temperature and precipitation variables relative to their 2001 levels. Darker shadings represent positive and negative contributions that are statistically significant at a 95% confidence level.

There are two important implications from the underlying heterogeneity in the microeconomic impacts of weather shocks and their contribution to aggregate impacts. First, aggregating across this competing variation reduces the first-order aggregate impacts of weather shocks. When weather shocks to some spur aggregate growth while shocks to others slow aggregate growth, they, at least partially, negate the contributions of one another. This washout effect is exemplified well in the estimates for 2012. Second, this heterogeneity in microeconomic impacts could matter for aggregate impacts. Corollaries 1 and 2 show that non-linearities in aggregate impacts depend on heterogeneity in the microeconomic impact of local weather shocks. Thus, I next estimate the second-order aggregate impacts of weather shocks to determine their economic importance.

5.2 Second-order Impacts

I estimate the aggregate impact of weather shocks according to Equation 21, applying Propositions 5 and 6, which describe the second-order effect of idiosyncratic and correlated shocks, respectively. From these propositions, I find that the ability of labor to reallocate across industries and space can have an effect on aggregate impacts. I begin by assuming that there is no labor reallocation. Below I explore relaxing that assumption.

Figure 6 displays the aggregate economic impact of microeconomic weather shocks estimated up to a second-order assuming no labor reallocation. Like the first-order approximation, I find variations in the size of the aggregate impacts across the sample years. However, unlike the first-order approximation, I find that the second-order aggregate impacts are consistently negative across each sample year except 2017. The aggregate losses (gain) in each year are larger (smaller) in the second-order approximation than in the first-order approximation. This result is consistent with the theoretical finding that complementarities dampen positive shocks and amplify negative shocks, as illustrated in Figure 1.

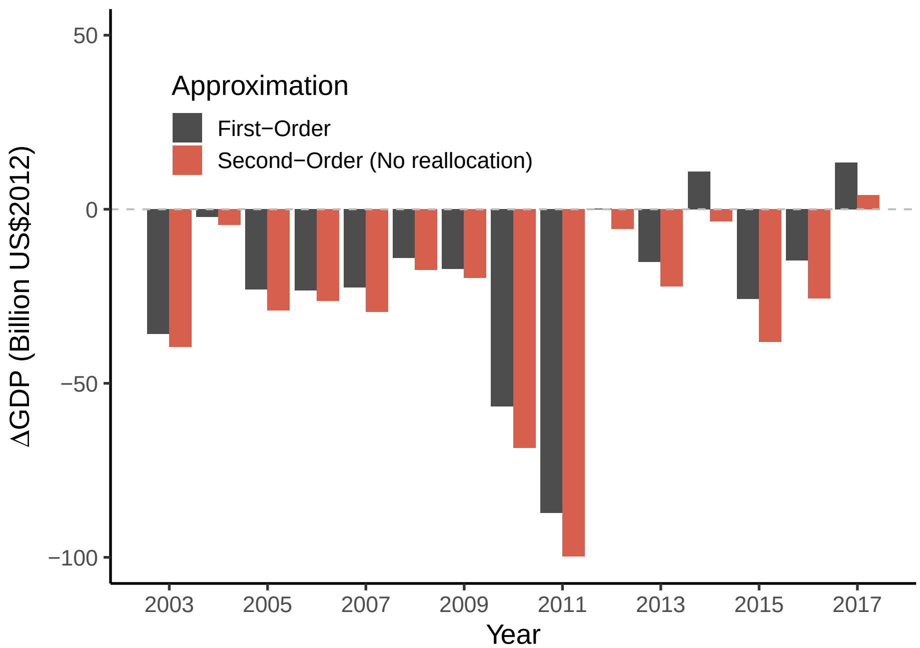


Figure 6: First-order and Second-order Estimates of Aggregate Impacts. Approximation of the aggregate impacts of weather shocks across county-industry producers up to a first- and second-order. Weather shocks are defined as changes in temperature and precipitation measures from their 2001 levels. For the second-order approximation, labor is assumed to be constrained so there is no potential for reallocation.

Summing over the sample period, I find that the second-order approximation of aggregate economic losses is around 33% larger than the first-order approximation. Accounting for non-linearities captured by the second-order terms is not just theoretically relevant, it is economically important. Ignoring these non-linearities substationally underestimates the aggregate economic losses. In a decomposition of the second-order terms, I find that the increase in aggregate losses is predominantly driven by non-linearities in economic production from Proposition 5 (Figure 11). The next largest contribution comes from non-linearities in the marginal effect of weather shocks. Non-linearities from cross-terms captured by Proposition 6 have little effect.

5.3 Effect of Labor Reallocation

From Corollary 2, the effect of labor reallocation on aggregate impacts depends on heterogeneity in microeconomic impacts of weather shocks. Here I estimate the potential effect of labor reallocation on the aggregate impacts of weather shocks given the heterogeneity in microeconomic impacts illustrated in Figure 5. I compare the cases of no labor reallocation and free labor reallocation. While these are extreme cases, such that the true costs of labor reallocation likely leave one somewhere between these two cases, this comparison provides an upper-bound estimate of the possible effect of free labor reallocation across industries and across space.

Figure 7 displays estimates of the change in aggregate impacts going from no labor reallocation to free labor reallocation. The change is measured as the percent reduction in the aggregate impacts of weather shocks for each year. The magnitude of the gains from free labor reallocation varies considerably across years. For example, in 2003 the gains from free labor reallocation are around 4% while in 2014 the gains are around 190%, sufficient to switch a negative aggregate impact into a positive aggregate impact. This variation is in part due to variation in the magnitude of the second-order effect terms from which labor reallocation effects derive and in part due to differences in the heterogeneity of microeconomic impacts across years. In 2017, the gain from labor reallocation is negative because allowing for labor reallocation increases an already positive aggregate impact. Thus, the level effect is still positive. Cumulatively across the sample period, allowing for free labor reallocation reduces the negative aggregate impact of weather shocks by around 10%. This suggests, given the inherent variability of weather shock impacts, that the ability of factors of production to flexibly reallocate at low costs can be an important economic mechanism to adapt to climate change.

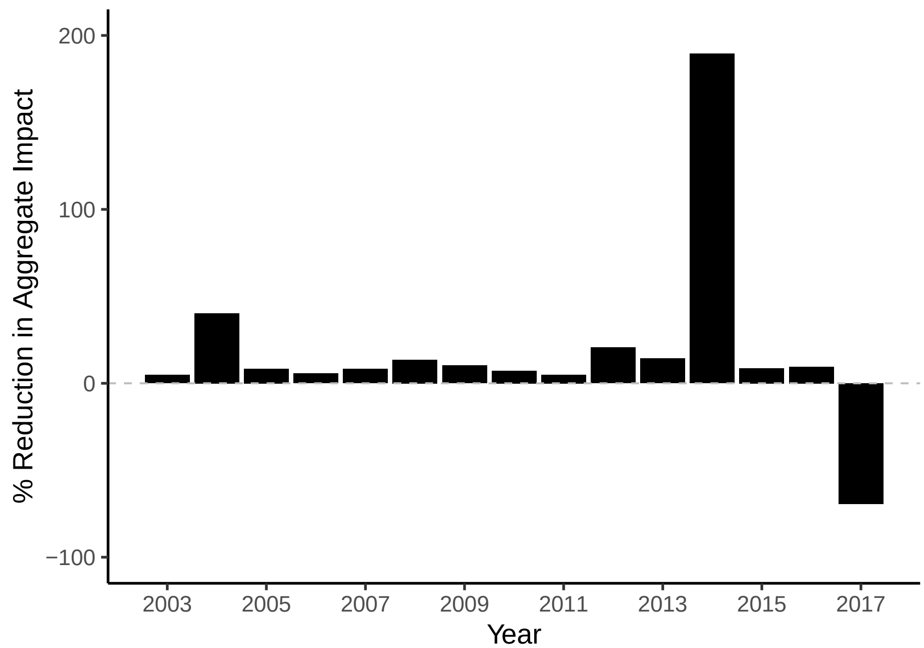


Figure 7: Effect of Labor Reallocation. Percent change in aggregate impacts for second-order approximation with free labor reallocation versus with no labor reallocation. For years 2003 to 2016, a positive reduction reflects a reduction of the negative aggregate impact. In 2017, a negative reduction reflects an amplification of the positive aggregate impact.

6 Role of Micro-level Heterogeneity

In the previous section, I find empirical evidence supporting the economic importance of the theoretical findings in Corollaries 1 and 2. Heterogeneity in weather shock impacts across space and industries interacts with non-linearities in production to increase aggregate economic losses by 33% over the sample period. And, given this heterogeneity, allowing for labor reallocation can reduce these aggregate impacts by 10% over the sample period. In this section, I examine these empirical findings more closely by exploring the importance of different sources of heterogeneity. Specifically, I consider heterogeneity in industrial response to weather shocks and heterogeneity in weather shocks.

6.1 Heterogeneity in Industrial Response

First, I consider heterogeneity in the industrial composition of the United States. Figure 2**(a)** provides suggestive evidence of the variation in industrial composition across the United States. Further, from Figure 3, I find that different industries have different sensitivities to weather shocks, both in magnitude and the shape of the relationship. I estimate the aggregate impacts of weather shocks according to Equation (21) using the industry-specific response functions. Then I use the pooled response function and compare estimates.

Row 1 of Table 1 shows that accounting for heterogeneity in the industry-specific response functions matters. Ignoring this source of heterogeneity by using a pooled response function increases aggregate economic losses, both to a first-order and second-order approximation. The second-order approximation increases less than the first-order approximation, which indicates that the effect of non-linearities diminishes when heterogeneity is removed. This is consistent with the theory in Corollary 1. Removing heterogeneity likewise substantially reduces the potential gains from labor reallocation. This is consistent with the theory in Corollary 2.

Table 1: Effect of Heterogeneity

Source of Heterogeneity	Δ FO Impact (%)	Δ FO+SO Impact (%)	Δ Gains from Labor Reallocation (pp)
Industry Response	67%	58%	-8.5pp
Weather Distribution	-41%	-46%	-6.8pp
Industry and Total Weather	-68%	-67%	-9.8pp

6.2 Heterogeneity in Weather

Next, I consider heterogeneity in the distribution of weather, both temporally and spatially. Figures 2b-d provide suggestive evidence of the variability of weather across both time and space. I estimate the aggregate impacts of weather shocks according to Equation (21) using the average temperature and precipitation across space for each year. Then I use the average temperature and precipitation across sample years for each region. Together, temperature and precipitation are constant within a year and constant across space. I compare this to estimates with heterogeneity.

Row 2 of Table 1 shows that accounting for variability in weather also matters. Ignoring the heterogeneity of local weather underestimates aggregate economic losses, both in a first-order and second-order approximation. The first-order approximation of aggregate impacts is reduced because averaging weather variables minimizes extremes that often drive microeconomic impacts. Further, averaging out variability in weather reduces the heterogeneity in microeconomic impacts, so the second-order impacts are reduced even further. Removing variability in weather across space and time likewise reduces the potential gains from labor reallocation.

6.3 All Weather and Industrial Response Heterogeneity

Finally, I simultaneously remove weather heterogeneity, both temporal and spatial, and heterogeneity in industrial response. I average temperature and precipitation across space and time and apply the pooled response functions. In this scenario, the microeconomic impacts of weather shocks are equivalent across all county-industry pairs are identical by definition. I have removed all heterogeneity.

Row 3 of Table 1 shows that the cumulative effect of ignoring all relevant heterogeneity. This greatly decreases the aggregate economic losses, both a first-order and second-order approximation. Removing spatial and temporal variation in the distribution of weather sets daily temperatures around 15°C, close to the peak of the pooled response function. As a result, changes in temperature have a small marginal effect on productivity. Removing all sources of heterogeneity also reduces the second-order impacts. Finally, gains from reallocation are completely eliminated as no heterogeneity at the microeconomic level remains.

7 Conclusions

Quantifying the economic impacts of climate are critical to determining appropriate policy to mitigate climate change. In this paper, I develop an economic theory of weather shock impacts that reflects the reality that weather shocks are inherently local and variable and that there will be variation in the response to weather shocks across industries and across space. To formulate this, I develop a general equilibrium theoretical model where weather shocks can only *directly* impact the productivity of local producers and that those direct impacts can vary.

A key finding of the theoretical model is that variability in the microeconomic impacts of weather shocks can have economic consequences. First, in the presence of production networks or common labor markets, local weather shocks have indirect spillover effects throughout the economy. Empirical estimates that try to identify the relationship between economic outcomes and weather shocks must account for these spillovers or focus on economic primitives, such as productivity, to avoid bias in their estimates. Second, when there are non-linearities in production from complementarities, these non-linearities interact with variability in microeconomic weather shock impacts with consequences for aggregate impacts. These are overlooked in models with log-linear production technologies. Third, the ability of labor to reallocate as a factor of production can moderate aggregate impacts when there is variability in microeconomic weather shock impacts. This can be a useful adaptation mechanism.

I use an empirical setting of the United States to determine the economic importance of the last two of these theoretical insights. I estimate the microeconomic impact of weather shocks on labor productivity across 14 NAICS 2-digit industries across counties composing the continental United States and aggregate them according to my economic theory. I find that non-linearities raise the aggregate impacts of weather shocks by 33% and that labor reallocation can reduce these aggregate impacts by 10%. Empirical estimates of the aggregate impacts of weather shocks substantially underestimate these impacts if they do not account for complementarities or ignore underlying variability in local weather and the relationship between weather shocks and productivity.

The model developed in this paper provides flexible basis for future analyses of aggregate climate impacts and to draw climate policy insights. Some possibilities for future work building on the model developed in this paper include considering additional factors of production beyond labor, expanding the empirical analysis beyond the United States, using regional input-output networks to analyze spillovers in economic impacts and regional outcomes, and developing a dynamic version of the model to construct projections of future climate impacts.

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The Network Origins of Aggregate Fluctuations. *Econometrica*, 80(5):1977–2016.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2017). Microeconomic origins of macroeconomic tail risks. *American Economic Review*, 107(1):54–108.

Armington, P. S. (1969). A theory of demand for products distinguished by place of production. *Staff Papers*, 16(1):159–178. Publisher: Springer.

Atalay, E. (2017). How Important Are Sectoral Shocks? *American Economic Journal: Macroeconomics*, 9(4):254–280.

Auffhammer, M., Hsiang, S. M., Schlenker, W., and Sobel, A. (2013). Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Review of Environmental Economics and Policy*, 7(2):181–198.

Baqaee, D. R. (2018). Cascading failures in production networks. *Econometrica*, 86(5):1819–1838.

Baqaee, D. R. and Farhi, E. (2019). The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem. *Econometrica*, pages 1155–1203.

Blackburn, C. J. and Moreno-Cruz, J. (2021). Energy efficiency in general equilibrium with input–output linkages. *Journal of Environmental Economics and Management*, 110:102524.

Boehm, C. E., Flaaen, A., and Pandalai-Nayar, N. (2018). Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tōhoku Earthquake. *The Review of Economics and Statistics*, 101(1):60–75.

Burke, M., Davis, W. M., and Diffenbaugh, N. S. (2018). Large potential reduction in economic damages under UN mitigation targets. *Nature*, 557(7706):549–553.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, 8(3):106–40.

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

Center for International Earth Science Information Network (2005). Gridded Population of the World (GPW), v3.

Colmer, J. (2018). Weather, Labor Reallocation and Industrial Production: Evidence from India. Technical Report dp1544, Centre for Economic Performance, LSE.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy*, 124(1):205–248.

Cruz, J.-L. and Rossi-Hansberg, E. (2021). The Economic Geography of Global Warming.

Damania, R., Desbureaux, S., and Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *Journal of Environmental Economics and Management*, 102:102335.

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

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

Deschênes, O. and Greenstone, M. (2007). The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review*, 97(1):354–385.

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

Gouel, C. and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, 106:102408.

Graff Zivin, J. and Neidell, M. (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics*, 32(1):1–26.

Hulten, C. R. (1978). Growth accounting with intermediate inputs. *The Review of Economic Studies*, 45(3):511–518.

Jerch, R., Kahn, M. E., and Lin, G. C. (2020). Local public finance dynamics and hurricane shocks. Working Paper, National Bureau of Economic Research.

Jones, B. F. and Olken, B. A. (2010). Climate Shocks and Exports. *American Economic Review*, 100(2):454–459.

Lemoine, D. (2020). General equilibrium rebound from energy efficiency innovation. *European Economic Review*, 125:103431.

Letta, M. and Tol, R. S. (2019). Weather, climate and total factor productivity. *Environmental and Resource Economics*, 73(1):283–305.

Long, J. B. and Plosser, C. I. (1983). Real Business Cycles. *Journal of Political Economy*, 91(1):39–69.

Park, R. J., Goodman, J., Hurwitz, M., and Smith, J. (2020). Heat and learning. *American Economic Journal: Economic Policy*, 12(2):306–39.

Rudik, I., Lyn, G., Tan, W., and Ortiz-Bobea, A. (2021). Heterogeneity and Market Adaptation to Climate Change in Dynamic-Spatial Equilibrium. *Working Paper*.

Schlenker, W. (2020). Daily Weather Data for Contiguous United States (1950-2019).

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598.

Appendices

A Proofs

Proof of Proposition 1.
Following the assumption of competition, prices are equal to the marginal cost of production. This gives

$$p_{ir}^{1-\sigma} = \frac{\gamma_{ir}}{A_{ir}(W_r)^{1-\sigma}} w^{1-\sigma} + \sum_{j=1}^{N} \sum_{s=1}^{R} \omega_{jsir} p_{js}^{1-\sigma}$$

Rearranging this equation by moving the second term on the right-hand side to the left-hand side, I solve for a vector of prices in matrix form.

Starting with the production market clearing condition, $y_{ir} = c_{ir} + \sum_{j=1}^{N} \sum_{s=1}^{R} x_{ir,js}$, I multiply both sides of the equation by prices p_{ir}^{σ}. This gives

$$p_{ir}^{\sigma} y_{ir} = p_{ir}^{\sigma} c_{ir} + \sum_{j=1}^{N} \sum_{s=1}^{R} p_{ir}^{\sigma} x_{ir,js}$$

Substituting the equations for final and intermediate input demand from Equations (2) and (5), I rearrange the equation and convert to matrix form to solve for a vector of sales.

For equilibrium wages, I first consider the case of full labor reallocation. Starting with the labor market clearing condition $\bar{L} = \sum_{i=1}^{N} \sum_{r=1}^{R} L_{ir}$ I substitute the conditional labor demand equation from Equation 6. Rearranging, I solve for the equilibrium economy-wide wage rate. Next, consider the case of no labor reallocation. Here wages are given as the marginal revenue product of labor for each producer.

Proof of Proposition 2
Own Sales Effect.
Independent of assumptions about labor reallocation, the *Own Sales Effect* can be written

as

$$
\begin{aligned}
\frac{\mathrm{d}\log(p_{ir}^{\sigma}y_{ir})}{\mathrm{d}W_r} &= \frac{\mathrm{d}\log\Big((\boldsymbol{\mathcal{L}\alpha})_{ir}M\Big)}{\mathrm{d}W_r} \\
&= \frac{\mathrm{d}\log(M)}{\mathrm{d}W_r} \\
&= \lambda_{ir}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}
\end{aligned}
$$

The final step comes from applying the equivalence between aggregate income and aggregate output and applying the proof of Proposition 4 below.

Own Wage Effect.

Consider free labor reallocation for which there is a single wage rate, w, for the economy.

$$
\begin{aligned}
\frac{\mathrm{d}\log(w)}{\mathrm{d}W_r} &= \frac{\mathrm{d}(\frac{1}{1-\sigma})\log\Big((\boldsymbol{\mathcal{L}\alpha})\boldsymbol{\gamma}^{*}(\mathbf{W})\Big)}{\mathrm{d}W_r} \\
&= \lambda_{ir}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}
\end{aligned}
$$

Alternatively when there is no labor reallocation,

$$
\begin{aligned}
\frac{\mathrm{d}\log(w_{ir})}{\mathrm{d}W_r} &= \frac{\mathrm{d}\frac{1}{\sigma}\log\Big(\gamma_{ir}^{*}(W_r)L_{ir}^{-1}p_{ir}^{\sigma}y_{ir}\Big)}{\mathrm{d}W_r} \\
&= \frac{\sigma-1}{\sigma}+0+\frac{\lambda_{ir}}{\sigma}
\end{aligned}
$$

Own Labor Effect.

Consider free labor reallocation.

$$
\begin{aligned}
\frac{\mathrm{d}\log(L_{ir})}{\mathrm{d}W_r} &= \frac{\mathrm{d}\log\Big(\gamma_{ir}^{*}(W_r)w_{ir}^{-\sigma}p_{ir}^{\sigma}y_{ir}\Big)}{\mathrm{d}W_r} \\
&= (\sigma-1)-\sigma\lambda_{ir}+\lambda_{ir} \\
&= (\sigma-1)(1-\lambda_{ir})
\end{aligned}
$$

Alternatively when there is no labor reallocation, the *Own Labor Effect* is by definition 0.

Proof of Proposition 3

Indirect Sales Effect.

Independent of assumptions about labor reallocation, the *Indirect Sales Effect* can be written as

$$\begin{aligned}\frac{\mathrm{d}\log(p_{ir}^{\sigma}y_{ir})}{\mathrm{d}W_r} &= \frac{\mathrm{d}\log\Big((\boldsymbol{\mathcal{L}\alpha})_{ir}M\Big)}{\mathrm{d}W_r} \\ &= \frac{\mathrm{d}\log(M)}{\mathrm{d}W_r} \\ &= \lambda_{ir}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}\end{aligned}$$

The final step comes from applying the equivalence between aggregate income and aggregate output and applying the proof of Proposition 4 below.

Indirect Wage Effect.

Consider free labor reallocation for which there is a single wage rate, w, for the economy.

$$\begin{aligned}\frac{\mathrm{d}\log(w)}{\mathrm{d}W_r} &= \frac{\mathrm{d}(\frac{1}{1-\sigma})\log\Big((\boldsymbol{\mathcal{L}\alpha})\boldsymbol{\gamma}^*(\mathbf{W})\Big)}{\mathrm{d}W_r} \\ &= \lambda_{ir}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}\end{aligned}$$

Alternatively when there is no labor reallocation,

$$\begin{aligned}\frac{\mathrm{d}\log(w_{js})}{\mathrm{d}W_r} &= \frac{\mathrm{d}\frac{1}{\sigma}\log\Big(\gamma_{js}^*(W_s)L_{js}^{-1}p_{js}^{\sigma}y_{js}\Big)}{\mathrm{d}W_r} \\ &= 0+0+\frac{\lambda_{ir}}{\sigma}\end{aligned}$$

Indirect Labor Effect.

Consider free labor reallocation.

$$\begin{aligned}\frac{\mathrm{d}\log(L_{js})}{\mathrm{d}W_r} &= \frac{\mathrm{d}\log\Big(\gamma_{js}^*(W_s)w_{js}^{-\sigma}p_{js}^{\sigma}y_{js}\Big)}{\mathrm{d}W_r} \\ &= -\sigma\lambda_{ir}+\lambda_{ir} \\ &= -\lambda_{ir}(\sigma-1)\end{aligned}$$

Alternatively when there is no labor reallocation, the *Own Labor Effect* is by definition 0.

Proof of Proposition 4.

Aggregate output of the economy is equal to the aggregate value added of all producers, $\mathcal{Y} = \sum_{i=1}^{N} \sum_{r=1}^{R} w_{ir} L_{ir}$. This gives

$$\frac{\mathrm{d} \log \mathcal{Y}}{\mathrm{d} W_r} = \frac{\mathrm{d} \log \left(\sum_{i=1}^{N} \sum_{r=1}^{R} w_{ir} L_{ir} \right)}{\mathrm{d} W_r}$$

For full labor reallocation this gives

$$\begin{aligned} \frac{\mathrm{d} \log \mathcal{Y}}{\mathrm{d} W_r} &= \frac{\mathrm{d} \log w}{\mathrm{d} W_r} + \frac{\mathrm{d} \log \sum_{i=1}^{N} \sum_{r=1}^{R} L_{ir}}{\mathrm{d} W_r} \\ &= \lambda_{ir} \frac{\mathrm{d} \log \big(A_{ir}(W_r) \big)}{\mathrm{d} W_r} + 0 \end{aligned}$$

For no labor reallocation,

$$\begin{aligned} \frac{\mathrm{d} \log \mathcal{Y}}{\mathrm{d} W_r} &= \frac{1}{M} \sum_{i=1}^{N} \sum_{r=1}^{R} \frac{\mathrm{d} w_{ir} L_{ir}}{\mathrm{d} W_r} \\ &= \lambda_{ir} \frac{\mathrm{d} \log \big(A_{ir}(W_r) \big)}{\mathrm{d} W_r} \end{aligned}$$

Proof of Proposition 5.

Taking the derivative of Equation (18) with respect to a weather shock in region r gives

$$\begin{aligned} \frac{\mathrm{d}^2 \log \mathcal{Y}}{\mathrm{d} W_r^2} &= \frac{\mathrm{d}}{\mathrm{d} W_r} \left(\lambda_{ir} \frac{\mathrm{d} \log \big(A_{ir}(W_r) \big)}{\mathrm{d} W_r} \right) \\ &= \frac{\mathrm{d} \lambda_{ir}}{\mathrm{d} W_r} \frac{\mathrm{d} \log \big(A_{ir}(W_r) \big)}{\mathrm{d} W_r} + \lambda_{ir} \frac{\mathrm{d}^2 \log \big(A_{ir}(W_r) \big)}{\mathrm{d} W_r^2} \end{aligned}$$

I begin with the case of full labor reallocation. The derivative of value added share for producer ir with respect to weather shock in region r is given as

$$\begin{aligned} \frac{\mathrm{d} \lambda_{ir}}{\mathrm{d} W_r} &= \frac{1}{\bar{L}} \frac{\mathrm{d} L_{ir}}{\mathrm{d} W_r} \\ &= \lambda_{ir} (1 - \lambda_{ir}) (\sigma - 1) \frac{\mathrm{d} \log \big(A_{ir}(W_r) \big)}{\mathrm{d} W_r} \end{aligned}$$

Substituting this back in gives the solution.

Next, consider the case of no labor reallocation. The derivative of value added share for producer ir with respect to weather shock in region r is given as

$$\frac{\mathrm{d}\lambda_{ir}}{\mathrm{d}W_r} = \frac{\mathrm{d}w_{ir}}{\mathrm{d}W_r} - \sum_{j=1}^{N}\sum_{s=1}^{R}\frac{\mathrm{d}w_{js}}{\mathrm{d}W_r}$$
$$= \lambda_{ir}(1-\lambda_{ir})(1-\frac{1}{\sigma})\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}$$

Substituting this back in gives the solution.

Proof of Proposition 6.

Taking the derivative of Equation (18) with respect to a weather shock in region s gives

$$\frac{\mathrm{d}^2\log\mathcal{Y}}{\mathrm{d}W_rW_s} = \frac{\mathrm{d}}{\mathrm{d}W_s}\left(\lambda_{ir}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}\right)$$
$$= \frac{\mathrm{d}\lambda_{ir}}{\mathrm{d}W_s}\frac{\mathrm{d}\log\big(A_{ir}(W_r)\big)}{\mathrm{d}W_r}$$

I begin with the case of full labor reallocation. The derivative of value added share for producer ir with respect to weather shock in region s is given as

$$\frac{\mathrm{d}\lambda_{ir}}{\mathrm{d}W_s} = \frac{1}{\bar{L}}\frac{\mathrm{d}L_{ir}}{\mathrm{d}W_s}$$
$$= -\lambda_{ir}\lambda_{js}(\sigma-1)\frac{\mathrm{d}\log\big(A_{js}(W_s)\big)}{\mathrm{d}W_s}$$

Substituting this back in gives the solution.

Next, consider the case of no labor reallocation. The derivative of value added share for producer ir with respect to weather shock in region s is given as

$$\frac{\mathrm{d}\lambda_{ir}}{\mathrm{d}W_s} = \frac{\mathrm{d}w_{ir}}{\mathrm{d}W_s} - \sum_{l=1}^{N}\sum_{t=1}^{R}\frac{\mathrm{d}w_{lt}}{\mathrm{d}W_s}$$
$$= -\lambda_{ir}\lambda_{js}(1-\frac{1}{\sigma})\frac{\mathrm{d}\log\big(A_{js}(W_s)\big)}{\mathrm{d}W_s}$$

Substituting this back in gives the solution.

Proof of Corollaries 1 and 2

I assume a common weather shock to all regions that has a homogenous affect on all producers. That is, $\frac{\mathrm{d}\log\left(A_{js}(W_s)\right)}{\mathrm{d}W_s} = \frac{\mathrm{d}\log\left(A_{js}(W_s)\right)}{\mathrm{d}W_s}$ for all $\forall i \in \{1,...,N\}, r \in \{1,...,R\}$ and $j \in \{1,...,N\}, s \in \{1,...,R\}$.

Consider the first terms on the right-hand side of Equations (19) and (20). Noting that $\sum_{js}\lambda_{js} = 1$, aggregating the first term of the correlated shock over $js \neq ir$ under the assumption of a homogenous productivity shock gives

$$\sum_{js\neq ir} -\lambda_{ir}\lambda_{js}(\sigma-1)\frac{\mathrm{d}\log\left(A_{js}(W_s)\right)}{\mathrm{d}W_s}\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r} = \\ -\lambda_{ir}(1-\lambda_{ir})(\sigma-1)\left(\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r}\right)^2$$

for full labor reallocation. For no labor reallocation, the result is

$$\sum_{js\neq ir} -\lambda_{ir}\lambda_{js}(1-\frac{1}{\sigma})\frac{\mathrm{d}\log\left(A_{js}(W_s)\right)}{\mathrm{d}W_s}\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r} = \\ -\lambda_{ir}(1-\lambda_{ir})(1-\frac{1}{\sigma})\left(\frac{\mathrm{d}\log\left(A_{ir}(W_r)\right)}{\mathrm{d}W_r}\right)^2$$

Substituting this result into Equation (21), it is clear that the first terms of the second-order impacts cancel out in the second-order expansion. This leaves the first-order impacts and the second-order impact of non-linearities in the response of productivity to weather shocks for a common shock with homogeneous microeconomic impacts.

B Data

B.1 Economic Data

Here I provide more information about data used in the analysis. The 2-digit NAICS industry classifications are given in Table 2.

Table 2: List of Industries

NAICS Code	Industry Description
11	Agriculture, forestry, fishing, and hunting
21	Mining
22	Utilities
23	Construction
31-33	Manufacturing
42	Wholesale trade
44-45	Retail trade
48-49	Transportation and warehousing
51	Information
52-53	Finance, insurance, real estate, rental, and leasing
54-56	Professional and business services
61-62	Educational services, health care, and social assistance
71-72	Arts, entertainment, recreation, accommodation, and food services
81	Other services, except government
G	Government

B.1.1 Labor Productivity Growth Measure

The BEA does produce a measure of labor productivity at the county-industry-level of resolution. Thus, I use data provided by the BEA to construct a novel spatially- and industrially-resolute measure of labor productivity growth. Starting with the assumption of perfect competition, which implies that labor is compensated its marginal product, setting wages equal to the marginal revenue product of labor gives

$$\begin{aligned} w_{irt} &= p_{irt}\frac{\partial y_{irt}}{\partial L_{irt}} \\ &= \left[\gamma^*_{ir} L^{-1}_{ir} p^{\sigma}_{ir} y_{ir}\right]^{\frac{1}{\sigma}} \end{aligned}$$

Rearranging and solving for productivity gives

$$A_{irt}(W_{rt}) = \gamma^{\frac{1}{1-\sigma}} \left(\frac{w^{\sigma}_{irt} L_{irt}}{p^{\sigma}_{irt} y_{irt}}\right)^{\frac{\sigma}{\sigma-1}}$$

Taking the difference with respect to the previous period of the log of this equation for productivity gives the measure of growth in productivity.

$$\Delta \log(A_{irt}) = \frac{\sigma}{\sigma-1}\Delta \log\left(\frac{w_{irt} L_{irt}}{p_{irt} y_{irt}}\right) + \Delta \log\left(\frac{p_{irt} y_{irt}}{L_{irt}}\right) - \Delta \log\left(p_{irt}\right)$$

$$\Delta \log(A_{irt}) = \frac{\sigma}{\sigma-1}\Delta \log\left(\frac{w_{irt}L_{irt}}{p_{irt}y_{irt}}\right) + \Delta \log\left(\frac{p_{irt}y_{irt}}{L_{irt}}\right) - \Delta \log\left(p_{irt}\right) \tag{25}$$

Thus, constructing a measure of labor productivity growth requires data on labor compensation, gross output, labor input, prices, and the elasticity of substitution. Data on labor compensation comes from BEA data on annual personal income. Data on labor input comes from BEA data on total full-time and part-time employment data. Gross output and prices are only available aggregated to the industry level. Thus, I assume gross output for each county-industry pair is proportional to county-industry value-added, $p_{irt}y_{irt} = p_{rt}y_{rt} \times \frac{\text{VA}_{irt}}{\text{VA}_{rt}}$, and that changes in county-industry prices are directly reflected by changes in aggregate industry prices. Data on industry level output and prices come from BEA industry gross output and price index data. I choose an elasticity of substitution of $\sigma = 0.5$ following empirical evidence (Atalay, 2017; Boehm et al., 2018).

B.2 Weather Data

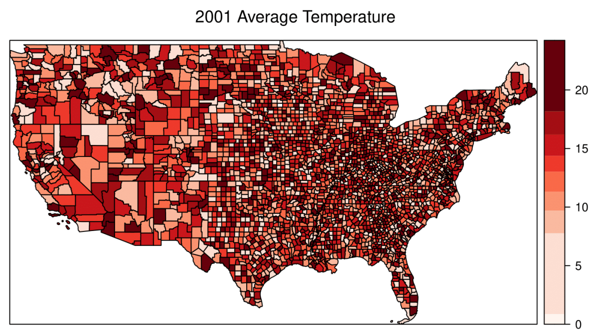
Here I provide more information about the economic and weather data used in the analysis through some basic summary statistics.

Table 3: Summary Statistics

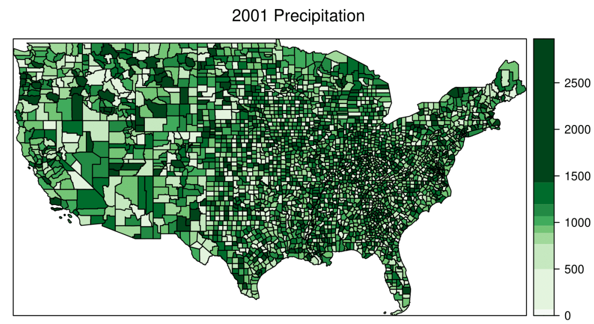
Panel A: Economic	Mean	Std. Dev.	Min	Max
Population	98,646.1	315,531.8	55	10,120,540
Value Added per capita ($US2012)	3,288.8	94,562.4	0	48,648,796
Growth Value Added per capita	0.00910	0.287	-7.898	9.359
Growth Labor Productivity	0.0109	0.346	-7.898	7.963
Panel B: Weather	Mean	Std. Dev.	Min	Max
Cum. Daily Temperature (°C)	4,684.7	1,662.6	-69.30	9,263.2
Cum. Daily Temperature Sq.	101,053.8	36,844.9	18,074.5	242,821.8
Cum. Daily Temperature Cub.	2,136,609.3	1,111,300.0	-91,844.6	6,678,533.2
Cum. Daily Precipitation (mm)	1,009.6	405.8	20.38	4,149.0
Cum. Daily Precipitation Sq.	18,179.0	13,395.6	27.10	224,040.9

Unit of observation is a county-industry in a year. There are 3,080 counties, 14 industries, and 17 years, totalling 785,400 observations.

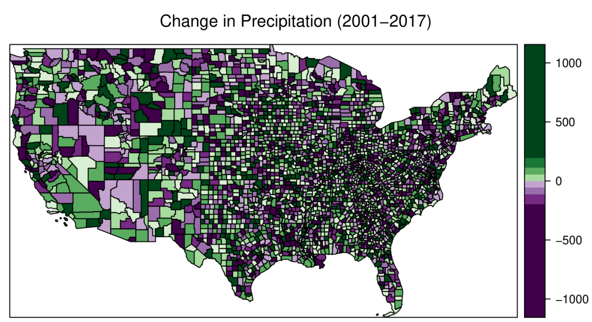
Figure 8 displays additional information about the distribution of temperature and precipitation across counties. Panel **(a)** shows the distribution of average daily temperature in 2001. Panel **(b)** shows the distribution of average daily precipitation in 2001. Panel **(c)** shows the change in average daily precipitation over the sample period. These figures reinforce that there is heterogeneity in climate and weather shocks across the United States when analyzed at a more resolute scale.



(a)



(b)



(c) Average Temperature Distribution.

Figure 8: Additional Descriptive Statistics.

C Additional Empirical Results

In this section, I provide some additional results.

Figure 9 displays the marginal effect of precipitation on labor productivity growth for the pooled estimate and by industry classification. Estimates and their respective 95% confidence intervals are plotted relative to peak (minimum) growth precipitation.

Figure 10 displays the contributions to aggregate economic impacts up to a first-order by county-industries for each year in the sample period.

Figure 11 displays the results of calculating the second-order aggregate impacts of microeconomic shocks in each year. Specifically, I break down the second-order impacts into their underlying components: the second-order idiosyncratic impact deriving from changes in the value added shares, the second-order correlated impact deriving from changes in the value added shares, and the second-order impact deriving from non-linearities in the responsiveness of labor productivity growth the weather shocks.

Figure 12 displays the alternative results for the first-order and second-order estimates of the aggregate impacts of weather shocks for elasticities of substitution **(a)** $\sigma = 0.3$ and **(b)** $\sigma = 0.9$. The different elasticities are used in both the construction of labor productivity growth, changing the estimating microeconomic response functions, and in the construction of the second-order approximation of aggregate impacts. A lower elasticity of substitution reduces the aggregate impacts while a higher elasticity increases the aggregate impacts. This is due to a weaker (stronger) microeconomic response function with the lower (higher) elasticity. While the quantitative values differ with elasticity assumption, the takeaways of the paper are consistent. Accounting for second-order effects meaningfully increase aggregate impacts while allowing for reallocation reduces aggregate impacts.

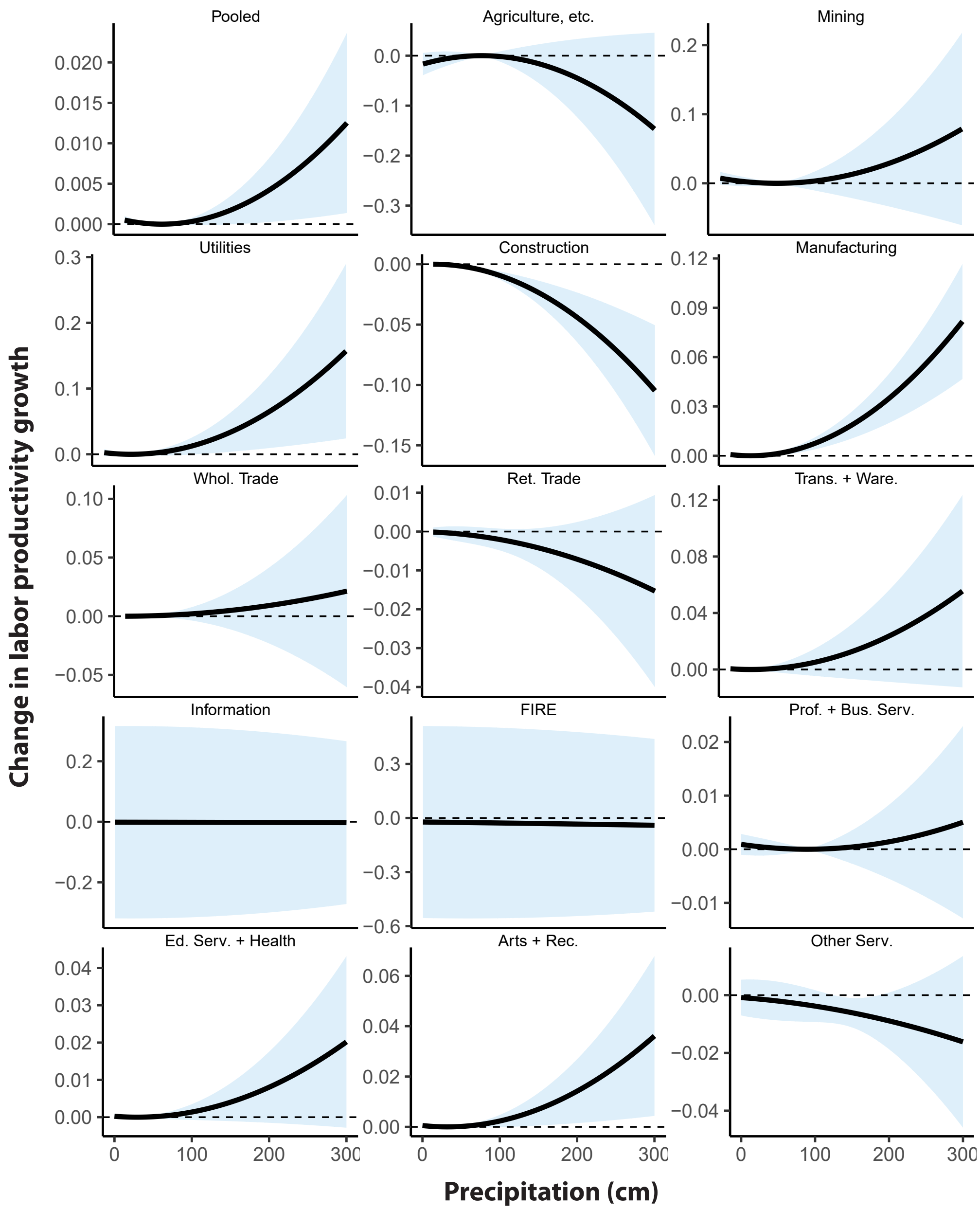


Figure 9: Microeconomic precipitation response functions. Empirically estimated marginal labor productivity growth-precipitation response function for pooled response and by industry classification. Marginal effects plotted relative to peak growth precipitation for pooled response, around 50cm. Lines represent mean estimates and blue fill represents 90% confidence interval using clustered standard errors.

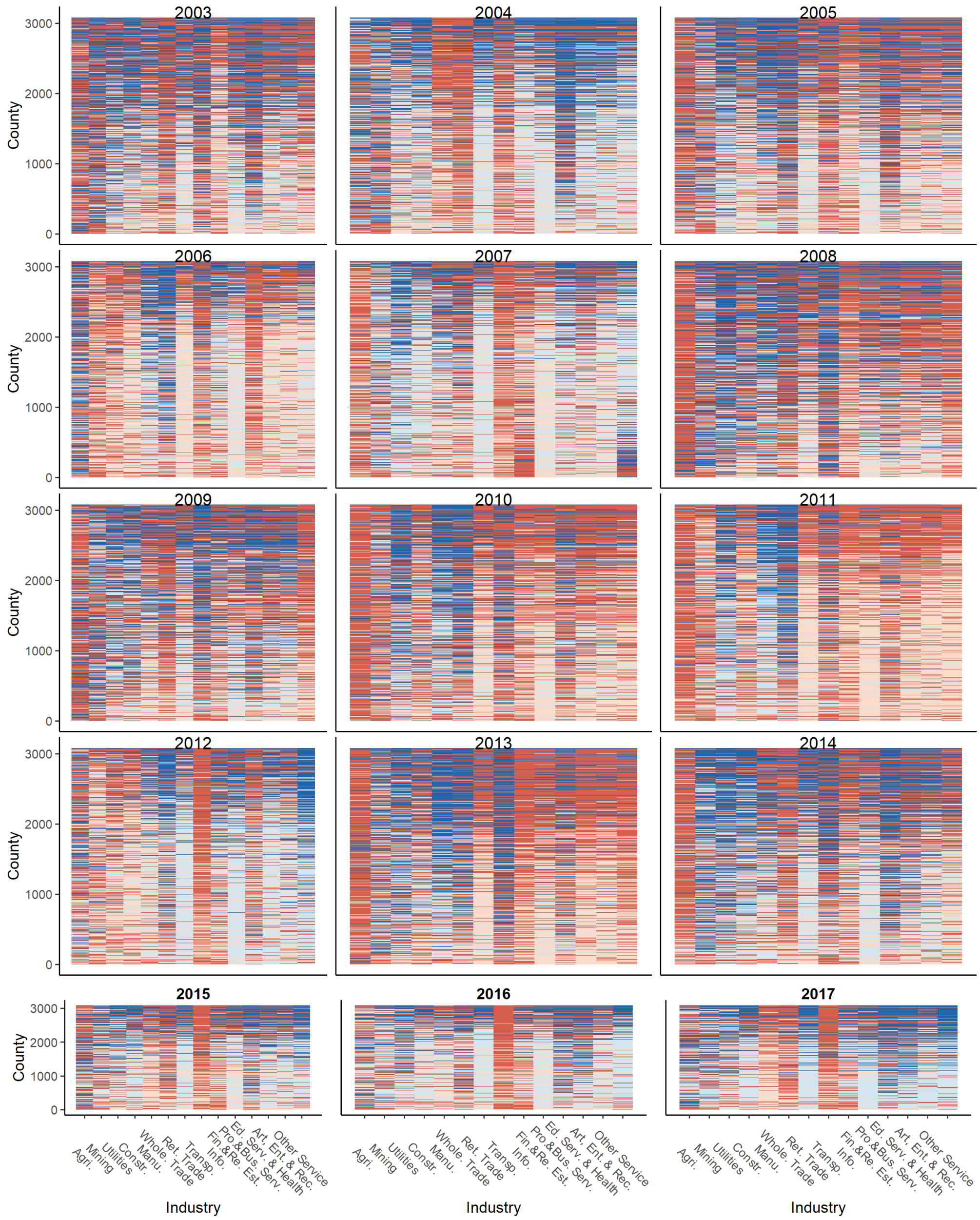


Figure 10: County-industry contributions to first-order aggregate impacts by year.

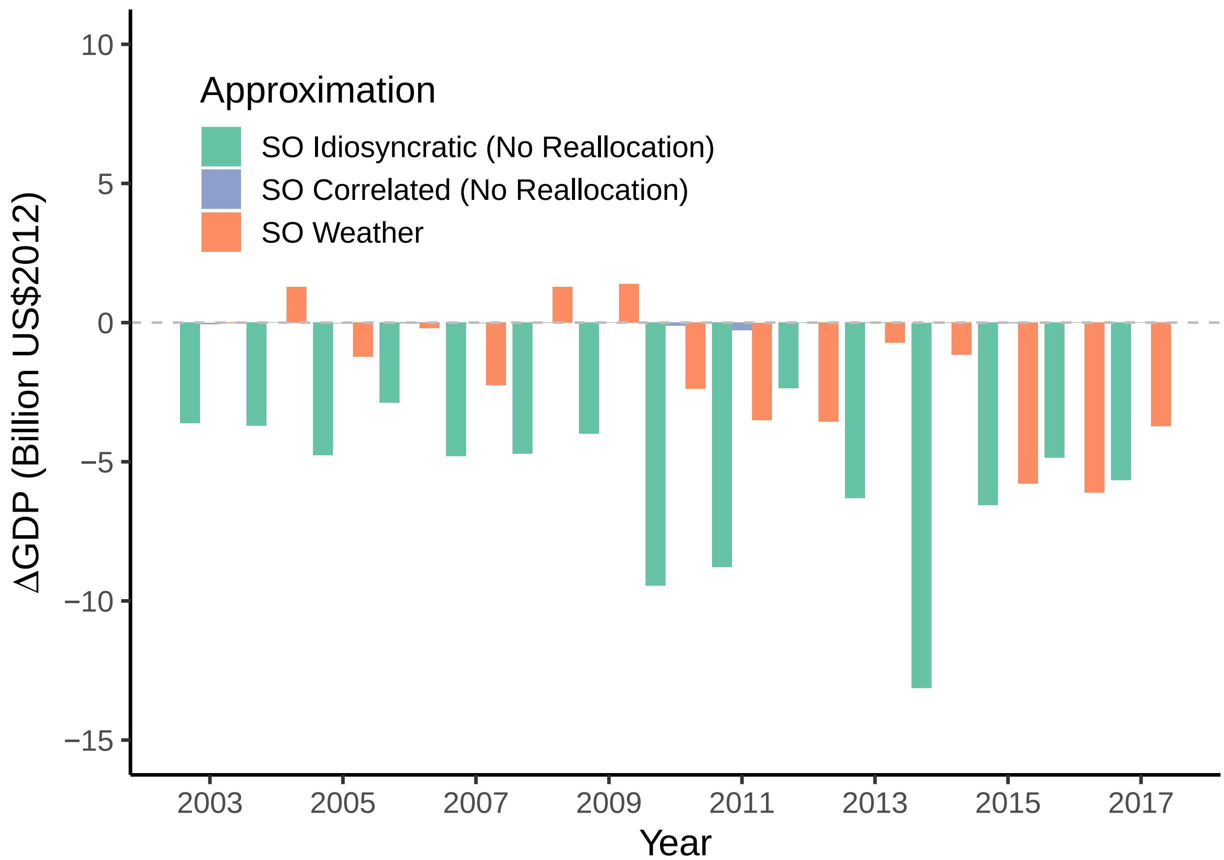
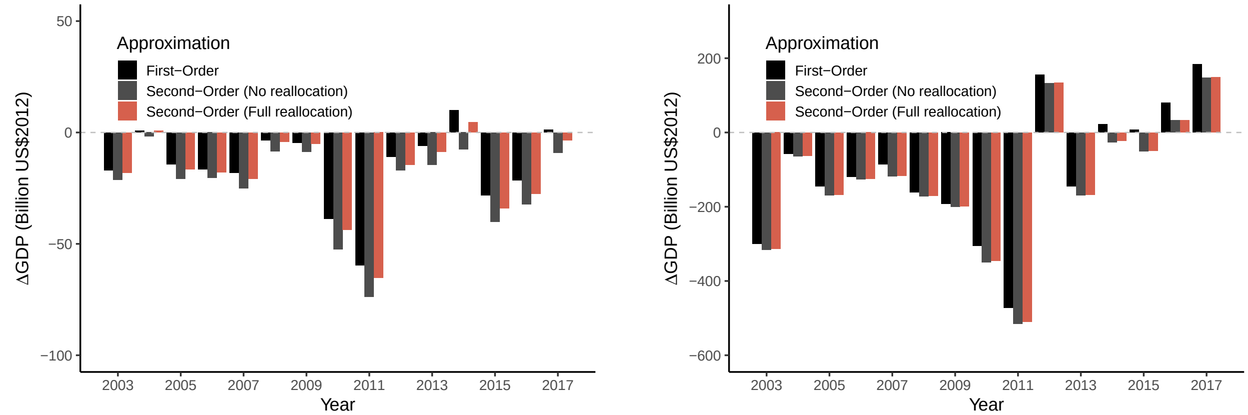


Figure 11: Composition of the Second-Order Impact. SO Idiosyncratic reflects the aggregation of the first term on the right-hand side of Equation (19). SO Correlated reflects the aggregation of the first term on the right-hand side of Equation (20). SO Weather reflects the aggregation of the second term on the right-hand side of Equation (19).



(a) $\sigma = 0.3$ **(b)** $\sigma = 0.9$

Figure 12: Aggregate Impact Estimates for Different Elasticities. Aggregate impacts estimated up to a first-order and up to a second-order both with full reallocation and no reallocation for elasticities of substitution **(a)** $\sigma = 0.3$ and **(b)** $\sigma = 0.9$. The different elasticities are used in both the construction of labor productivity growth, changing the estimating microeconomic response functions, and in the construction of the second-order approximation of aggregate impacts. While the quantitative results vary from the results in the text for $\sigma = 0.5$, the qualitative takeaways are the same.