Impact of Extreme Weather Events on the U.S. Domestic Supply Chain of Food Manufacturing

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Abstract

In the United States, like in other countries around the world, agri-food security is challenged by a growing population and less predictable weather conditions. Extreme weather events such as droughts and extreme rainfall increase the volatility of agricultural yield for producers. This means changes in comparative advantages, in the domestic trade of agricultural products and, in turn, in the manufacturing of food products since the former are necessary inputs in the production of the latter. We investigate how locally sourced agricultural inputs are substituted with inputs imported from other states. We construct a structural framework for manufactured food production as a function of labor, capital and agricultural inputs. We first estimate a model for the trade in animals and fish (SCTG01), one for cereal grains (SCTG02), and one for the other agricultural products (SCTG03) which is composed mainly of fruits, vegetables and soybeans. It will constitute the first step of our two-stage analysis. In the second stage, we will estimate a nested production function for processed food at the state level. Our combination of two structural models allows us to quantify the extent to which food manufacturing in any single state is dependent on local weather shocks affecting the production of locally grown inputs and of weather shocks taking place in faraway locations where the remaining inputs are imported from. The findings provide details on the key linkages in the domestic food supply chain and are informative for the design of policies aiming at mitigating the impacts of climate change on the U.S. food and agricultural sector.

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1 Introduction

In the United States, like in other countries around the world, agri-food security is challenged by a growing population and less predictable weather conditions. While climate change has already led some areas of the United States to experience more frequent and intense extreme weather events, the change is expected to accelerate in the decades to come (IPCC, 2022). Extreme weather events such as droughts and extreme rainfall increase the volatility of agricultural yield for producers (Deschênes & Greenstone, 2012; Lesk et al., 2016; Schlenker & Roberts, 2009) which may mean changes in comparative advantages, in the domestic trade of agricultural products (Burke & Emerick, 2016; Costinot et al., 2016; Dall'Erba et al., 2021; Magalhães Vital et al., 2022) and, in turn, in the manufacturing of food products since the former are necessary inputs in the production of the latter (Cheng et al., 2022; Malik et al., 2022; McCorriston & Sheldon, 1991; Rosenzweig & Parry, 1994). A recent example is drought-struck Nebraska who in 2012 had to import 2.65 times as many agricultural commodities from other U.S. states than under regular weather conditions in order to feed its livestock and maintain its food manufacturing activities. For states who do not specialize in agriculture but need to maintain their purchases of crops and livestock for food manufacturing and for their citizens, this type of event might mean more competition and higher prices for food, even if the said weather event took place thousands of miles from them (Bertassello et al., 2023; Gouel & Laborde, 2021; Laber et al., 2023; Malik et al., 2022; Reimer & Li, 2010).

Central to society's capacity to address these challenges is the ability of trade to guarantee the resiliency of supply chains from producers to the agri-food industry and then to final consumers. For the current trade economics literature that highlights trade as a market-mediated strategy to recover the aftermath of a shock on the supply of agricultural and food commodities, the focus has traditionally been more at the international level (Costinot et al., 2016; Ferguson & Gars, 2020; Gouel & Laborde, 2021; Magalhães Vital et al., 2022; Reilly & Hohmann, 1993; Schenker, 2013). Yet, in spite of the United States producing up to 87 percent of its agricultural commodities for the domestic market (Dall'Erba et al., 2021), there is a paucity of studies focusing on U.S. domestic flows. The few exceptions include Dall'Erba et al. (2021), (Burke & Emerick, 2016), and (Nava et al., 2023).

Compared to the international level, the domestic focus this manuscript adopts means that the capacity of adaptation is limited by the range of nationally produced crops, country-wide weather conditions, and the national transportation network. However, the trade impact principles remain the same: production losses following a sudden drought or a flood are substituted with imports, hence leading to trade creation or diversion (Dall'Erba et al., 2021; Ferguson & Gars, 2020; Gouel & Laborde, 2021). As a result and in the short-run, trade has the potential to mitigate the disruptive effects of extreme weather. However, in the long run, climate change is expected to drive adaptation in the agricultural sector through efforts such as crop-rotation, adoption of heat- and drought-resistant plant and livestock varieties, livestock herd reductions in drought years, shifting production northward and towards the Colorado Rockies (McCarl et al., 2016; Miao et al., 2016). This challenge highlights the critical need to properly address the complex impact of extreme weather events on the trade of agricultural commodities and, in turn, on the manufacturing of food in the United States.

In order to understand the vulnerability and resilience of the U.S. agri-food supply chain to a changing climate, we investigate the extent to which locally sourced agricultural inputs are substituted with inputs imported from other states. We construct a structural framework for the production of manufactured food as a function of labor, capital and agricultural inputs. The key novelty is that we assume that there is constant elasticity of substitution (CES) between agricultural inputs that are sourced locally and imported from other states. This framework is firmly grounded in the theory of the gravity model of bilateral trade where inputs sourced from different trading partners have Armington-CES (Yotov et al., 2016). The bottom line is that we investigate interregional and intersectoral relationships embedded in the production process of the downstream sector by structurally combining the gravity model of trade and CES production function, an endeavor that has never been done before. A similar work by (Boehm et al., 2019) analyzes how an exogenous shock from the Japanese input sector is transmitted downstream in the United States. However, this study estimates the firm-level constant elasticity of substitution with respect to only observed inputs and does not link cross-country trade flows with the gravity model.

The application will allow us, first, to answer how extreme weather shocks (drought and wetness measured through SPEI, the Standardized Precipitation Evapotranspiration Index) in both origin and destination states affect the interstate of livestock and staple crops. This gravity model estimation relies on an extensive state-to-state panel dataset of the Freight Analysis Framework (FAF) which records all domestic flows categorized by Standard Classification of

Transported Goods (SCTG) sector codes. As such, we will estimate a model for the trade in animals and fish (SCTG01), one for cereal grains (SCTG02), and one for the other agricultural products (SCTG03) which is composed mainly of fruits, vegetables and soybeans. It will constitute the first step of our two-stage analysis.

In the second stage, we will estimate a nested production function for processed food at the state level. We will account for the elasticity of substitution between locally produced and imported agricultural inputs from the CES input production function. Our combination of two structural models allows us to quantify the extent to which food manufacturing in any single state is dependent on local weather shocks affecting the production of locally grown inputs and of weather shocks taking place in faraway locations where the remaining inputs are imported from.

The rest of this paper is organized as follows: Section 2 describes how we combine the structural equations of two distinct models, one based on trade gravity and one based on nested production function, in order to include both interregional and intersectoral linkages in the analysis of food manufacturing. Section 3 presents the data and shows some statistics of their distribution over our study period. Section 4 presents the estimates of the effect of extreme weather on agricultural trade and on food manufacturing. This section displays some robustness checks as well. Finally, section 5 summarizes the results and provides some concluding remarks.

2 Theoretical Framework

In this section, we formulate our modelling approach of a production function with inputs that are sourced from another sector and another location. The properties of the aggregate production function follow a Cobb-Douglas (CD) production function with labor, capital, and the *input aggregate* from the upstream sector. Within the *input aggregate*, inputs from different locations are set to have the properties of CES preferences straight from the structural gravity framework of trade (Anderson & Van Wincoop, 2003).

The final output of manufactured food Y^F follows a CD production function of aggregate capital K^F(superscript F denotes food manufacturing), aggregate labor L^F as well as a composite of agricultural inputs I^A (superscript A denotes agricultural production) needed in the food manufacturing sector. Following the structural gravity framework, we set the composite of inputs as a CES aggregate of agricultural inputs that are produced locally I_j^A and that are sourced from all other states I_{-j}^{A} (Armington, 1969). This is expressed as:

$$Y_j^F = A^F \left(L_j^F\right)^{\alpha} \left(K_j^F\right)^{\beta} (I^A)^{\gamma} \tag{1}$$

where A^F is the technological productivity of the manufactured food sector, $\alpha, \beta\ and\ \gamma$ are factor shares, and I^A is noted as (2). By setting the aggregate CD production function, we assume that capital, labor, and the agricultural input aggregate have an elasticity of substitution equal to 1, which means that changes in their relative price will not vary the ratio of these inputs.

$$I^A = \left[\delta\left(I_j^A\right)^{\theta} + (1-\delta)\left(I_{-j}^A\right)^{\theta}\right]^{\frac{1}{\theta}} \tag{2}$$

We are interested in estimating the substitution parameter θ to attain the elasticity of substitution between locally sourced and imported agricultural inputs $\sigma_\theta = 1/(1-\theta)$. The elasticity of substitution is nonnegative as defined by production theory. In addition, agricultural inputs from different sources are expected to be substitutes ($\sigma_\theta > 1$). Traded agricultural inputs are assumed homothetic and common across states. The parameter δ is the share of I_j^A within the aggregate measurement of agricultural input. Section 2.1. below will explain how to measure I_j^A and I_{-j}^A while Section 2.2. will cover the food production function (equation 1) with CES between agricultural inputs (equation 2).

2.1. Agricultural inputs based on the gravity model of trade

2.1.1. Structural model

Agricultural inputs that enter the manufactured food production process (1) require from us to distinguish local from imported inputs. It is accomplished by relying on a state-to-state structural gravity model of trade as described in Anderson & Van Wincoop (2003). Equations (3a) and (3b) reflect how agricultural inputs produced locally, I_j^A, correspond to the intrastate trade, and inputs sourced from elsewhere I_{-j}^A are the sum of all interstate trade imported from all other states.

$$I_j^A = I_{ij}^{AF}, \qquad i = j \tag{3a}$$

$$I_{-j}^A = \sum_i I_{ij}^{AF}, \qquad \forall\, i \neq j \tag{3b}$$

$$I_{ij}^{AF} = \frac{X_i^A Y_j^F}{X} \left(\frac{t_{ij}}{\Pi_i \mathrm{P}_j}\right)^{1-\sigma_\rho} \tag{4}$$

In equation (4), I_{ij}^{AF} is the interstate trade of agricultural commodities from origin state i used by destination state j for food manufacturing; X_i^A is the production of agriculture in the exporting state i; Y_j^F is the total expenditure of the manufactured food sector in importing state j while $X = \sum_i X_i$ is total agricultural output. The exporting state's size X_i^A is defined as (5a) and the importing state's size Y_j^F is defined as (5b):

$$X_i^A = f\left(S_i^A, Z_i^A\right) \tag{5a}$$

$$Y_j^F = f\left(S_j^A, Z_j^A, Z_j^F\right) \tag{5b}$$

We consider the situation where extreme weather shock S^A is given to the size terms of the importing and exporting states. There is no equivalent S^F term needed since food manufacturing activities take place indoor and thus are not subject to a direct detrimental effect of weather. Trade for agricultural inputs is dependent on weather shocks both at origin and destination as well as on the capacity of exporters to produce agricultural commodities (Z_i^A), on the importers' capacity to produce local agricultural goods (Z_j^A) and on the demand for agricultural commodities to be used as intermediate inputs for manufactured food or to be consumed by households (Z_j^F). The expected impact of extreme weather shocks on I_{ij}^{AF} has been documented in Dall'erba *et al*. (2022): for the exporters of agricultural goods, production losses following a weather shock S_i^A would mean less available output to be exported X_i^A and/or relying on stocks for exports. For importers, production losses following a shock S_j^A are substituted with imports, hence creating trade Y_j^F . This means that the elasticity of substitution σ_θ between locally produced and imported agricultural inputs changes in the event of extreme weather disruption taking place at the point of origin, of destination or in both locations.

The second term of expression (4) are trade cost terms that include bilateral t_{ij} and multilateral trade frictions for the exporting Π_i and importing P_j state. Bilateral frictions include state-to-state factors that can impede or encourage trade between any trading partners. For international relations, such factors include trade policies, tariffs, and any economic, geographical, and cultural determinants of trade relations. In a domestic setting, such factors include distance between states, shared border, and within-state effects. Multilateral resistance terms measure the state's ease or impediment to market access as defined as:

$$\Pi_i^{1-\sigma_\rho} = \sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma_\rho} \frac{Y_j}{X} \qquad (6a)$$

$$P_j^{1-\sigma_\rho} = \sum_i \left(\frac{t_{ij}}{\Pi_i}\right)^{1-\sigma_\rho} \frac{X_i}{X} \qquad (6b)$$

In equation (6a) and (6b), Π_i is the outward multilateral resistance for the exporting state, P_j is the inward multilateral resistance for the importing state, and the equations are the weighted averages of the bilateral and multilateral trade frictions of the exporting state i and importing state j. Each trading partner is weighed based on the expenditure and production of the trading partner. σ_ρ is the CES-Armington elasticity of substitution between goods from different exporting states. Note that this elasticity of substitution σ_ρ is different from the one in equation (2): while σ_ρ in the gravity model captures the substitution between all possible destinations of the exporting states, the substitution σ_θ captures the interaction between local versus imported inputs only.

Taking the log of equation (4) in a panel setting measured over years t and across agricultural commodities k gives us an estimable specification:

$$lnI_{ijkt}^{AF} = lnX_{ikt}^{A} + lnY_{jkt}^{F} - lnX_{kt} + (1-\sigma_\rho)lnt_{ij} - (1-\sigma_\rho)ln\Pi_{ikt} \qquad (7)$$
$$-(1-\sigma_\rho)ln\mathrm{P}_{jkt} + \epsilon_{ijkt}$$

where ϵ_{ijkt} is the error term. Because the impacts of extreme weather shocks on agricultural trade is subsumed if we estimate the specification of the structural model directly, we will instead estimate equation (7) using a reduced-form approach as outlined in Section 2.1.2.

2.1.2. Empirical model

The reduced-form approach involves approximating each of the exporter- and importer-size, and trade cost terms as a function of observable variables (Anderson & Van Wincoop, 2003). Exporter- and importer-size terms consist of:

$$X_{ikt} = f(lnD_{ikt}^{A}, lnW_{ikt}^{A}, lnG_{ikt}^{A}, lnT_{ikt}^{A}, lnR_{ikt}^{A}) \qquad (8a)$$

$$Y_{jkt} = f(lnD_{jkt}^{A}, lnW_{jkt}^{A}, lnG_{jkt}^{F}, lnT_{jkt}^{A}, lnR_{jkt}^{A}, lnPop_{jt}^{A}) \quad (8b)$$

where drought D_{ikt}^{A} and wetness W_{ikt}^{A} are the two (growing season) weather variables of which mean and extreme values traditionally affect crop and livestock production; G_{ikt}^{A} is the production of agricultural commodities in the exporting state representing the exporters' capacity to produce agricultural goods; T_{ikt}^{A} is the growing degree days of the growing season, and R_{ikt}^{A} is the precipitation during the growing season. The same corresponding variables are included for the importer $j's$ size terms. Note that the importers' G_{jkt}^{F} is the GDP of food and beverages sector of the importing state representing the importers' demand for agricultural commodities to be used as inputs for manufactured food products. Since the GDP of food and beverages is the intermediate demand for agricultural commodities, it only partially represents the state-level demand. Hence, population Pop_{jt}^{A} is included to capture household demand.

Our bilateral trade costs consists of:

$$t_{ij} = f(lnDist_{ij}, C_{ij}, H_{ij}) \quad (9)$$

where $Dist_{ij}$, C_{ij}, and H_{ij} capture the distance, neighbor and home-effect, respectively.

Since Π_i and P_j have no explicit solution, we approximate the multilateral resistance terms (MRTs) following Baier & Bergstrand (2009) to work around identification issues. Empirical practice fully controls for both outward and inward MRTs with the use of exporter-time and importer-time fixed effects to avoid omitted variable bias (Yotov *et al*., 2016). However, this approach will subsume all factors that vary along the exporter-time and importer-time dimensions, including the extreme weather shocks. Instead, we approximate time-varying MRTs are as a function of production- and consumption-shared weighted average of bilateral factors – distance, neighbor and within-state factor variable.

We estimate two main specifications separately for each agricultural commodity: animals and fish ($k = 1$), cereal grains ($k = 2$) and other agricultural goods ($k = 3$). Our first empirical specification is equation (10). Since our analysis focus includes the role of locally produced agricultural inputs on the production of food manufacturing, we include terms related to within-state weather as:

$$I_{ijkt}^{A} = \exp [\alpha_{1k}^{home} lnD_{ikt}^{A} \times I(i = j) + \alpha_{1k}^{orig} lnD_{ikt}^{A} \times I(i \neq j) + \alpha_{1k}^{dest} lnD_{jkt}^{A} \times I(i \neq j) \quad (10)$$
$$+ \alpha_{2k}^{home} lnW_{ikt}^{A} \times I(i = j) + \alpha_{2k}^{orig} lnW_{ikt}^{A} \times I(i \neq j) + \alpha_{2k}^{dest} lnW_{jkt}^{A} \times I(i \neq j)$$

$$
\begin{aligned}
&+ \alpha_{3k}^{orig} lnG_{ikt}^{A} + \alpha_{3k}^{dest} lnG_{jkt-1}^{F} \\
&+ \alpha_{4k}^{home} lnT_{ikt}^{A} \times I(i = j) + \alpha_{4k}^{orig} lnT_{ikt}^{A} \times I(i \neq j) + \alpha_{4k}^{dest} lnT_{jkt}^{A} \times I(i \neq j) \\
&+ \alpha_{5k}^{home} lnT_{ikt}^{A} \times I(i = j) + \alpha_{5k}^{orig} lnR_{ikt}^{A} \times I(i \neq j) + \alpha_{5k}^{dest} lnR_{jkt}^{A} \times I(i \neq j) \\
&+ \alpha_{6k}^{dest} lnHH_{jt}^{A} + f\left(lnDist_{ij}, C_{ij}, H_{ij}\right) + MRT_{ijkt} \\
&+ \mu_{ij} + \mu_{CZi,t} + \mu_{CZj,t} + \epsilon_{ijkt}]
\end{aligned}
$$

where I_{ijkt} is the volume of traded agricultural goods. The first term with parameter α_{1k}^{home}, captures the impact of the within-state drought indicating whether locally traded commodity (or commodity produced that is consumed within a state) reflects the drought impact on available local agricultural products (as represented by the interaction with indicator variable $I(i = j)$). The drought-effect on exports (α_{1k}^{orig}) and imports (α_{1k}^{dest}) are drought terms interacted with indicator variable $I(i \neq j)$ to reflect the effect of drought on all intrastate trade. Similarly, we have parameter α_{2k}^{home} to represent within-state wetness effect for the interacted term of wetness and the within-state indicator $I(i = j)$. Wetness related terms, that are associated with parameters α_{2k}^{orig} (for exports) and α_{2k}^{dest} (for imports), from other states are reflected as an interaction of the wetness variable and intrastate indicator $I(i \neq j)$. We include similar interacted terms for within state and intrastate temperature and precipitation. $f\left(lnDist_{ij}, C_{ij}, H_{ij}\right)$ is a summation function of trade cost variables and parameters, MRT_{ijkt} is also a summation function of each MRT variables and the parameters. Equation (10) also includes the importer and exporter climate-zone by year fixed effects $\mu_{CZi,t}$ and $\mu_{CZj,t}$ which control for any variation of within climate zone characteristics including price changes. And ϵ_{ijkt} is the error term.

The second specification involves defining drought as extreme and mild conditions as in (11):

$$
\begin{aligned}
I_{ijkt}^{A} = \exp [&\alpha_{1k}^{ext\_home} lnD_{ikt}^{A} \times I(i = j) \times I\left(\left|SPEI_{ijkt}\right| > 1.3\right) \\
&+ \alpha_{1k}^{mild\_home} lnD_{ikt}^{A} \times I(i = j) \times I\left(\left|SPEI_{ijkt}\right| < 1.3\right) \\
&+ \alpha_{1k}^{ext\_orig} lnD_{ikt}^{A} \times I(i \neq j) \times I\left(\left|SPEI_{ijkt}\right| > 1.3\right) \\
&+ \alpha_{1k}^{mild\_orig} lnD_{ikt}^{A} \times I(i \neq j) \times I\left(\left|SPEI_{ijkt}\right| < 1.3\right) \\
&+ \alpha_{1k}^{ext\_dest} lnD_{ikt}^{A} \times I(i \neq j) \times I\left(\left|SPEI_{ijkt}\right| > 1.3\right) \\
&+ \alpha_{1k}^{mild\_dest} lnD_{ikt}^{A} \times I(i \neq j) \times I\left(\left|SPEI_{ijkt}\right| < 1.3\right)
\end{aligned} \tag{11}
$$

$$+ \alpha_{2k}^{home} lnW_{ikt}^{A} \times I(i = j) + \alpha_{2k}^{orig} lnW_{ikt}^{A} \times I(i \neq j) + \alpha_{2k}^{dest} lnW_{jkt}^{A} \times I(i \neq j)$$
$$+ \alpha_{3k}^{orig} lnG_{ikt}^{A} + \alpha_{3k}^{dest} lnG_{jkt-1}^{F}$$
$$+ \alpha_{4k}^{home} lnT_{ikt}^{A} \times I(i = j) + \alpha_{4k}^{orig} lnT_{ikt}^{A} \times I(i \neq j) + \alpha_{4k}^{dest} lnT_{jkt}^{A} \times I(i \neq j)$$
$$+ \alpha_{5k}^{home} lnT_{ikt}^{A} \times I(i = j) + \alpha_{5k}^{orig} lnR_{ikt}^{A} \times I(i \neq j) + \alpha_{5k}^{dest} lnR_{jkt}^{A} \times I(i \neq j)$$
$$+ \alpha_{6k}^{dest} lnHH_{jt}^{A} + f\left(lnDist_{ij}, C_{ij}, H_{ij}\right) + MRT_{ijkt}$$
$$+ \mu_{ij} + \mu_{CZi,t} + \mu_{CZj,t} + \epsilon_{ijkt}]$$

where $I\left(\left|SPEI_{ijkt}\right| > 1.3\right)$ (or $I\left(\left|SPEI_{ijkt}\right| < 1.3\right)$) is an indicator variable for extreme (or mild) drought conditions with drought SPEIs above (or below) the threshold of 1.3. The parameter for the first term $\alpha_{1k}^{ext\_home}$(or $\alpha_{1k}^{mild\_home}$) reflects the extreme (or mild) drought-effect on locally produced agricultural product k. For extreme (or mild) drought-effect on exports, we include $\alpha_{1k}^{ext\_orig}$ (or $\alpha_{1k}^{mild\_orig}$). Similarly, for extreme (or mild) drought-effect on imports, we include parameters $\alpha_{1k}^{ext\_dest}$ (or $\alpha_{1k}^{mild\_dest}$).

For both equations (10) and (11), the bilateral pair fixed effects provide important benefits in identifying the relationship between trade volume and extreme weather variables. First, using state-pair fixed effects accounts for the unobservable linkages between the endogenous trade policy covariate and the error term in gravity regressions (Baier & Bergstrand, 2007). Second, the pair fixed effects provide a flexible and comprehensive account of the effects of all time-invariant bilateral trade costs because pair fixed effects carry systematic information about trade costs, other than those captured by distance, shared-border, and home-effect, in addition to the information captured by the standard gravity variables.

2.2. Production function of manufactured food

Following the CD theoretical framework, the empirical specification for the second stage is the nested production function for manufactured food. Equations (1) and (2) that include the three agricultural input commodities and the importer and time dimension is expressed as equations (12) and (13), respectively. Production of manufactured food is a CD-aggregate of labor, capital, and k subaggregates of agricultural inputs (*k=3*) as:

$$Y_{jt} = AL_{jt}^{(1-\beta-\sum_k \gamma_k)} {K_{jt}}^{\beta} {I_{jkt}}^{\sum_k \gamma_k} \tag{12}$$

Within each input aggregate, we assume CES between local and imported inputs as:

$$I_{jkt} = [\hat{I}_{j=i,kt}{}^{\theta_k} + (\sum_{j\neq i}^{48} \hat{I}_{i,kt})^{\theta_k}]^{\frac{1}{\theta_k}} \tag{13}$$

Transforming equations (12) and (13) in log format leads to:

$$lnY_{jt} = a_j + a_t + \left(1 - \beta - \sum_{k=1}^{3} \gamma_k\right) lnL_{jt} + \beta lnK_{jt} \tag{14}$$

$$+ \sum_{k=1}^{3} \gamma_k \left[\frac{1}{\theta_k} \ln\left(\hat{I}_{j=i,kt}{}^{\theta_k} + \left(\sum_{j\neq i}^{48} \hat{I}_{i,kt}\right)^{\theta_k}\right)\right] + \varepsilon_{jt}$$

In equation (14), Y_{jt} is total production of the food manufacturing sector; L_{jt} measures the aggregate labor; K_{jt} is the aggregate capital; $\hat{I}_{j=i,1,t}$ is the local animals and fish input or the predicted within-state animals and fish from equation (10) or (11); $\hat{I}_{j=i,2,t}$ is the predicted local cereal grains input; $\hat{I}_{j=i,3,t}$ is the predicted value of remaining agricultural inputs locally grown; $\sum_{j\neq i} \hat{I}_{i,1,t}$ is the imported animals and fish or the sum of all the predicted interstate goods flowing into state j estimated from the first stage; $\sum_{j\neq i} \hat{I}_{i,2,t}$ is for the imported cereal grains; ; $\sum_{j\neq i} \hat{I}_{i,3,t}$ is for the imported remaining agricultural goods. The parameter β is the output elasticity of capital, γ_1 is the output elasticity of the subaggregate animals and fish input, γ_2 is the output elasticity of the subaggregate of cereal grains input, γ_3 is the output elasticity of other agricultural goods input. The parameter θ_k is the substitution parameter between local and imported commodity k. a_j is the state fixed effect, a_t is the year fixed effect. ε_{jt} is the error term.

The purpose is to identify the substitution parameter between local and imported agricultural inputs within the commodity-type aggregate. On the other hand, the CD specification of aggregate output for manufactured food assumes that the elasticity of substitution between each pair of aggregated capital, aggregated labor and sub-aggregate of agricultural commodities are all equal to 1. While this limits us from identifying the elasticity of substitution between some inputs, we are still able to attain the distributional revenue share between input categories by estimating α, β, and γ. Our setting is based on two reasons. First, animals and fish, cereal grains and other agricultural products (including vegetables and fruits) are hardly substitutable across commodity groups. Second, this setting is chosen to attain parsimony of estimation (Fuss *et al.*, 1978). If we set a nested CES production function where all the input categories are substitutable, we would have many more parameters to estimate. Since we are interested in the substitution between locally sourced and imported agricultural commodities only, we will focus on estimating the substitution parameter for each agricultural commodity. We also assume neutral technological change.

As in equation (13), we do not impose restrictions on the substitution parameter (θ) between local and imported agricultural inputs as our baseline specification. However, statistical tests show that we cannot reject that the substitution parameter is non-zero with our data. Similarly, the null hypothesis that the elasticity of substitution (σ_θ) is equal to one cannot be rejected. Thus, we present results for both when agricultural inputs (within each agricultural input aggregate, not the whole production function) are assumed CES and CD. For simulations in Section 4.3 on the drought-effect on manufactured food production are based on the estimates from the CD specification (Table 6). We do this because 1) tests reject the existence of substitution (or complementary) relationship between locally produced and imported inputs, and 2) the estimated output elasticities from both specifications are comparable. The estimation results based on our CES specification are presented in the Appendix (Table D7).

As a robustness check for the nonlinear estimation of the CES production function, we show the results after linearizing the nested production functional form (14) through a first-order approximation as in Kmenta (1967) and (Papageorgiou et al., 2017).

$$ln\left(\frac{Y_{jt}}{L_{jt}}\right) = a_j + a_t + \delta ln\left(\frac{K_{jt}}{L_{jt}}\right) + \sum_{k=1}^{3}\left[\pi_k ln\left(\frac{\hat{I}_{jkt}}{L_{jkt}}\right) + \rho_k ln\left(\frac{\widehat{M}_{jkt}}{L_{jkt}}\right) + \varphi_k ln\left(\frac{\widehat{M}_{jkt}}{\hat{I}_{jkt}}\right)^2\right] + \varepsilon_{jt} \quad (15)$$

where the predicted imports is $\widehat{M}_{jkt} = \sum_{j\neq i}^{48} \hat{I}_{ikt}$. The constraints are $\pi_k = \rho_k$. The distribution and substitution parameters in equation (14) can be retrieved from equation (15) where $\beta = \delta$, $\gamma = 2\pi$, $\theta_k = \varphi_k/8\pi_k$, and $\sigma_k = 1/(1-\varphi_k/8\pi_k)$ for each k.

3 Data

3.1 Gravity model of agricultural trade

The data on the state-to-state trade of animals and fish (SCTG01), cereal grains (SCTG02), and other agricultural products (SCTG03) come from the Freight Analysis Framework (FAF)[3] Version 5.5 (2023) built by the Bureau of Transportation Statistics. We compile a dataset based on the quinquennial U.S. domestic trade flows of the FAF for the five years between 1997 – 2017. The data we compile covers all interstate trade flows for 48 states across 5 years (34,560 data points)[4]. We also include intrastate flows for its benefits (Yotov, 2022). First, including intrastate flows is consistent with the theoretical framework of the gravity model and the production function in this study where destination states choose among locally grown and imported agricultural inputs. Second, including intrastate flows to some extent treats the bias in state-specific effects because differences in intrastate flows across states can represent variations in trade-related factors such as trade cost and size. In each case, we include the actual volume of trade flows from all modes of transportation (e.g., truck, rail, water and multiple modes). We exclude flows that enter or leave the United States so that we include only freight movements and agri-food production for the domestic market. All the measures are adjusted to 2012 U.S. dollars using the corresponding producer price index.

To measure the capacity to produce agricultural commodities of the exporting state, we use total production of agricultural commodities (SCTG01-03) calculated as the sum of the value of flows that are exported to all the states. For the importing states' demand of each agricultural commodity (SCTG01-03), we use the lagged production of the processed food sector. Production is measured as the GDP of food, beverages and tobacco (NAICS312) from the Bureau of Economic Analysis (BEA). Output is weighted to account for the flows of each agricultural commodity used for the production of processed food commodities (SCTG04-09) based on the percentage from Table 1. This shows the flow of SCTG01-03 to each category in SCTG04-09 based on the Input-Output table (IMPLAN, 2020). About 76.7 percent of animals and fish, 57.9 percent of cereal grains, and 33.7 percent of the rest of agricultural products are used as

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[3] We choose FAF over another widely used interstate trade data set, the Commodity Flow Survey (CFS), for several reasons. First, the CFS is collected by surveying only the firms from the shipping industry, and therefore does not represent the actual universe of U.S. trade flows. The Bureau of Transportation Statistics (BTS) puts together the CFS responses and the missing information from the Census Bureau and the Federal Highway Information (FHWA) for the FAF dataset. Second, the CFS does not sample trade flows for some sectors including agriculture. The FAF, on the other hand, incorporates shipments of agricultural industries with information from the United States Department of Agricultural National Agricultural Statistics Service (USDA NASS), and thus better represents shipments of crops and livestock. Another advantage of the FAF is that data over the years from 1997 to 2017 are comparable unlike the CFS for which there is extensive censoring for pre-2007 data.

[4] 48 states × 48 states × 5 years × 3 commodities = 34,560 data points

intermediate inputs in the industry. We use the data from the BEA instead of the sum of the traded flows from the FAF because we need the GDP for the manufactured food industry for every five years from 1996 to 2011[5]. However, the FAF documents data starting from 1997. The real values are deflated to 2012 U.S. dollars using the Implicit Price Deflator from the BEA.

While most agricultural commodities are used as inputs for the processed food sector, Table 1 shows that about 5.6-26.2 percent flows to households as final consumption. Demand by households (population size) is incorporated separately from industry demand. We use state population observations from the BEA as household consumption measure.

For extreme weather shocks, drought and wetness, we use the Standardized Precipitation Evapotranspiration Index (SPEI)[6] aggregated at the state level. We create the drought index as the absolute values of the negative measures of the SPEI and the wetness index as positive SPEIs. We then compute two weights with respect to time and space in order to aggregate daily/monthly measures to yearly data, and county-level measures to the state level. We use measurements during the growing season for each type of crop (USDA, 2022a); but for animals and fish (SCTG01), we use all-year-long SPEI values. We then aggregate county-level measurements to the state-level for each commodity using spatial weights based on farmland acres per county[7]. Using both spatial and temporal weights ensures that the commodity-specific SPEIs better resemble the climate conditions of the regions and seasons that they are actually grown and harvested in. For temperature, we aggregate monthly, county-level Growing Degree Days (GDD) to the annual state level. Yearly precipitation will be an aggregate of daily county-

[5] Production at the state level for all the industries classified by the North American Industry Classification System (NAICS) code is provided for every year from 1997 forward. For 1996, we use the concordance from the SIC to NAICS and the SIC classified production for the food and beverage industry the same way we did for constructing labor in the second stage.

[6] We obtain weather data from the ERA5-Land (Munõz Sabater, 2021) database which provides daily or monthly weather data at a spatial resolution of 4km from 1981 to 2019. SPEI is a standardized index which, for each locality, reports the deviation of current drought or wetness conditions in the region from the region's historical distribution of weather conditions, accounting for both precipitation and potential evapotranspiration (PET) in quantifying drought and wetness. The SPEI ranges from -3 to 3 where negative/positive values indicate dry/moist conditions for productivity in agriculture. The SPEIs are especially practical in relating drought and agriculture since growth in agriculture depends on the supply of water and atmospheric demand of water. Also, the standardized measures make it possible to compare the SPEI values across different times and places.

[7] The weights will be based on the farmland area of each product classified in SCTG02/03 from the USDA Farmland Service Agency (USDA FSA) (USDA, 2022b). For SCTG01, we use information from USDA NAAS Census of Agriculture on county-level total sales of each livestock product for the aggregation of county-level observations to the state level (USDA NASS, 2023). The data from the Census of Agriculture is a comprehensive count of U.S. farms and ranches that grows fruit, vegetables or food animals with more than $1,000 worth of raised and sold products.

level precipitation to the state level. The details on the weighing scheme for weather data are in the Appendix B.

We compute the MRT for each bilateral relationship including distance (or travel time), contiguity dummy and home-effect dummy. Distance between states is measured as the travel time of trucks for the shortest path between the most populated city of the origin and destination state. Travel time is calculated by Open Source Routing Machine (OSRM). For trade flows within a given state, the average shipment distance as reported by the CFS is used and averaged over all periods to avoid issues with geometric computation of within-state distance noted by Mayer and Head (2002). This is in line with previous domestic trade literature (Dall'erba *et al*., 2021) for which travel time is a more suitable proxy since it is a domestic setting where shipments by trucks are more prevalent (Hwang *et al*., 2021).

All the remaining variables used in the estimation of the gravity model are summarized in Table 2.

3.2 Food manufacturing production function

Our sample is composed of observations over the 48 continental U.S. states and every five years between 1997 and 2017. The time period is constrained by the availability of the trade flow data. We rely on three main data sources for the variables in the second stage. Data on aggregate production of food manufacturing is calculated from the FAF dataset. We begin by treating the FAF data by excluding any flows that are either imported or exported internationally. Next, we define production as the sum of all intrastate and interstate trade flows as domestic production is either used for intermediate consumption, final consumption or inventory, all of them being recorded through a flow to a destination. We do this process for both volume and value for each of the food commodities: animal feed (SCTG04), meat/poultry preparations (SCTG05), milled grains and bakery products (SCTG06), other prepared foods (SCTG07), alcoholic beverages (SCTG08), and tobacco products (SCTG09). Finally, we aggregate all the categories into a single food (SCTG04-09) category by state and year to create the aggregated production of agri-food products. We use the volume of production for our main analysis[8].

[8] Production of manufactured food and beverages from the BEA cannot be used as the dependent variable for the second stage because it is used to allocate national capital to the state level, and thus its use would result in perfect collinearity with computed capital. The value of production from the FAF is also used to estimate the second stage but results did not show robust findings that are in line with our assumptions.

For the data on labor, we use the total full-time and part-time employment for the two industries classified by the North American Industry Classification System (NAICS): food manufacturing (NAICS311) and beverage and tobacco product manufacturing (NAICS312). The BEA provides annual observations for the 50 states from 1998 onward. However, there are some undisclosed values we have to deal with. Details are in Appendix B.

Since the capital stock variable is not readily available at the state level and by sector, its construction requires a few steps. We follow the approach of Garofalo and Yamarik (2002) to allocate the capital stocks proportionally to each state's value-added for the food and beverage industry (Han & Lee, 2016; Maestas et al., 2023; Peri, 2012; Yamarik, 2013). We have two sources for national capital stock: the Federal Reserve Board (FRB, 2022) and the National Bureau of Economic Research and U.S. Census Bureau's Center for Economic Studies (NBER-CES) Manufacturing Industry Database[9] (Becker et al., 2021). The FRB documents manufacturing investment and capital stock in 2012 U.S. dollars that follow the six-digit 2017 NAICS definition of industries from 1952 to 2020 at the national level. We then allocate the national capital stock for each year across states in proportion to the value-added (BEA, 2021) in food, beverages and tobacco manufacturing. The value-added for the industry is from the BEA. We assume that all the states have the same capital-output (capital-labor) ratios for the manufacturing food industry because the ease of capital mobility across states for the industry leads to adjustment in the capital-labor ratio so that capital returns are equal across states (Peri, 2012).

When it comes to locally produced and imported intermediate crops and livestock inputs, their value corresponds to the sum of the predicted values calculated from the first stage. All the variables used in the food manufacturing production function are summarized in Table 3.

3.3 Summary statistics

Figure 1 graphs the national trends in SPEI for commodities 01 – 03. The year 2012 displays the lowest SPEI reflecting the enormous drought incidence in most of the Midwest. In 2017, both indices increased compared to 2012, but were still lower than the 1997 values. We now look at the SPEIs across the U.S. states during the historic drought in 2012.

[9] We use the national estimate of capital stock from the FRB because the NBER-CES data is missing the 2017 estimates for the capital stock of food and beverages and requires extrapolation. If we apply the growth rate of the FRB stock from 2016 to 2017 and estimate the production function with the NBER-CES capital stock the results are similar from those using the FRB numbers.

Figure 2 maps the SPEI of each state in 2007 and 2012. We chose these two years to see the changes in states that experienced intense drying conditions during the historic drought of 2012. Relative to 2007, a majority of the U.S. states were hit by the drought in 2012. And the 2012 drought is concentrated in the Midwest. Figure 2B depicts that Iowa, Illinois, Nebraska, Tennessee, Indiana, Ohio, and Kentucky experienced severe drought conditions (with $SPEI < -1$). These states happen to be the major players in the production of cereal grains. Figure 2C shows a similar story with midwestern states experiencing drought, but now the drought is more spread out towards the South and Southwest. For SCTG01, see Figure 2A.

Figure 3 shows the total food manufacturing production (commodities 04 – 09) at the state level. It is clear that California is a major producer with 172,999.166 million US$ of production on average for our sample period. Other states such as Texas (99,647.934 million $), Illinois (78,877.386 million $), and New York (71,658.178 million $) are also major producers of manufacturing food. Although not displayed here, we also graphed the agri-food production change from 2007 to 2012. In the absence of trade and therefore no substitutable imports, drought-struck states would face a shortage of inputs and thus produce less agri-foods. However, we found that there was a low rate of change showing that states maintained their 2007-level of agri-food output. What could have occurred is a trade diversion to source more agricultural products used for inputs in the manufactured food sector.

Figures 4 – 6 depicts the change in import ratio from 2007 to 2012 along with the total production of each agricultural commodity (01 – 03). We chose 2007 and 2012 for our reference years to observe the changes in each state's importing behavior relative to their locally sourced agricultural production before and after the major drought of 2012 (as seen in panel B of Figure 2A – 2C). Figure 4 panel A shows that states (e.g., Nebraska, Kansas, and Arizona) that experienced higher drought relative to 2007 imported more from other states. Nebraska increased its import ratio by about 385.16 percent even though it is already a high producing state (as seen in panel B) possibly to compensate for the loss of locally produced livestock (and fish) from severe drought. For commodity 1, some states clearly relied on production from other locations.

For cereal grains (SCTG02), Figure 5 panel A illustrates that the top consuming states, Iowa, Illinois, and Nebraska, all increased their imports relative to locally grown grains. The rate of increase was about 542.70 percent for Iowa, and 96.16 percent for Illinois, and 97.86 percent for Nebraska, hence showing that even the major producers of grains (as seen in panel B) compensated for their loss in local production by increasing their trade with other states. The total manufactured food output, on the other hand, did not increase as much in 2012.

Figure 6 panel A shows that most of the heat-struck producers of commodity 03 that used to rely less on imports in 2007 imported more in 2012. For Missouri, the increase rate was about 527.39 percent. Missouri decreased its imports from Nebraska to 1.11 from 417.80 kilo tons, and instead diverted its trade to Louisiana, North Dakota, Iowa, Illinois, Arkansas and Kansas for supply. Interestingly, these states produce less than California and Florida (as see in panel B). In sum, we observe a higher reliance on imports relative to locally grown agri-commodities in the face of severe drought. In addition, trade diversions to locations that experienced relatively less drought could be observed even though these locations are not the top producers of the commodity. This shows that the change in comparative advantages and therefore trade patterns is a more complex process that necessitates a more systematic analysis.

4 Results

4.1 Gravity model estimates

We estimated the gravity model of trade applying the Poisson Pseudo-Maximum Likelihood (PPML)[10] estimator (Santos Silva & Tenreyro, 2006, 2011). Table 4 reports the PPML estimates of equation (10) for the panel of 48 states and five years (1997, 2002, 2007, 2012, 2017). Table 5 reports the same estimates with extreme drought defined as SPEI lower than -1.3 and mild drought. The dependent variables are the volume of traded agricultural commodities. Each column reports the result of a different agricultural commodity regressed with the corresponding drought, wetness, GDD and precipitation variables.

The results display some notable features: first, we provide evidence of a positive impact of a drought in the destination state and imports of cereal grains (SCTG02 in column (2)). The reduced local supply that results from such an event is simply compensated by greater imports from other origin points. In addition, the results indicate a significant and detrimental impact of a

[10] The PPML estimator outperforms the OLS estimator to estimate the gravity model (Silva and Tenreyro, 2006; Yotov *et al*., 2016; Dall'erba *et al.,* 2021). First, estimating the OLS estimator will drop the zero trade flows leading to biased estimates. We are dealing with disaggregated trade by sector, and the proportion of zero trade flows for animals and fish (SCTG01), cereal grains (SCTG02), and other agricultural products (SCTG03) is 25 percent, 20 percent and 25 percent, respectively. Second, the presence of heteroskedasticity inherent in trade data leads to biased and inconsistent OLS estimates.

drought on the exports of cereal grains (SCTG02 in column (2)) and other agricultural products (SCTG03 in column (3)). These results confirm our expectations. A drought in the origin state corresponds to a loss in productivity and therefore to a lesser volume available for export. The relationship is not necessarily 1-to-1 as states can rely on storage from the previous year but, in the event of a drought, they would anyway serve the needs of the local market before exports. We do not find any statistically robust relationship between drought and animals and fish trade (SCTG01). This result might be attributable to SCTG grouping animals and fish in the same category and/or it could be due to the fact that a large amount of livestock raising takes place indoor where fans, misters and air conditioners are available (Schimmelpfennig *et al*., 1996). We also note the lack of significant impact of wetness.

A similar yet more clear relationship between drought and trade appears in Table 5, especially for category 03. In our previous result (Table 4), the positive relationship between drought and commodity 03 inflows are statistically significant at higher than 10 percent level. The drought-effect on imports becomes more pronounced for extreme drought conditions as shown in Table 5. Notably, a 1 percent increase in extreme drought in the destination state increases vegetables and fruits (including other agricultural products) by 0.652 percent. Another result to note is that the negative relationship between drought and commodity 03 exports becomes larger compared to our previous specification. These results are consistent with robustness checks in Appendix D.

The results confirm our expectations that the places producing more agricultural products export more. It seems to be particularly true for livestock production compared to crops. However, we do not find a clear relationship between exports and the lagged GDP of the food manufacturing sector and population in the destination states. Further analysis could assess the role of the GDP of each purchasing sector at destination.

Finally, we find a statistically significant role of growing degree days at origin and at destination on the export of cereal grains (SCTG02). These results, as well as the significant role of precipitation on exports of SCTG03 products, indicate that states engage in trade of agricultural commodities to benefit from the differences between their own and their partners' comparative advantages.

4.2 Production function estimates

We set the main specification for the processed food sector production that is CES in local and imported inputs and Cobb-Douglas in capital, labor, and input aggregates. We first run the NLS estimation of equation (14) without imposing restrictions on the elasticity of substitution[11]. We additionally run the regression for equation (14) where we impose CD on the elasticity of substitution (or equal to one). and then the OLS regression after linearizing the CES function as in equation (14).

The two-stage approach allows us to estimate the impact of weather shocks on the production of manufactured food as it occurs exclusively through trade. However, since trade is endogenous to the dependent variable in stage 2, we rely on a set of instruments in stage 1 that are defined by theory, that are statistically relevant (they influence trade) and that affect Y in stage 2 exclusively through trade. These instruments are the multilateral resistance terms as well as the weather conditions and production in the places of origin i. Table 6 reports the regression results for stage 2 after adopting the estimated value of the trade flows from stage 1 for inputs. More precisely, we use the sum of imports of SCTG01-03 products by category and imports from one's own state (intrastate trade). Column 1 reports the estimation results when we have extreme and mild drought in stage 1, and column 2 reports the regression results when we do not distinguish extreme to mild drought. The equation includes two-way fixed effects.

The results displayed in columns 1 and 2 indicate that the estimates of the distribution parameters are mostly significantly positive. First, we find a significant output elasticity of approximately 0.20 between production in the manufactured food sector and capital stock; whereas the elasticity of labor, at 0.59, is about 2.5 times larger. This result depicts how labor-intensive food manufacturing is, a result we expected and has been documented in Gandhi *et al.* (2020) and (Wahdat & Lusk, 2023)). Second, we find significant output elasticities for the agricultural input commodities. The estimates of SCTG02 commodities show an output elasticity (or marginal effect) of 0.057 which is similar to the significant elasticity of 0.054 for SCTG03 commodities (both at the 10% level). The elasticity of SCTG01 commodities is not significant though. We attribute this result to the fact that SCTG01 commodities are not used across all SCTG04-09 categories such as SCTG04 (animal feed), SCTG06 (milled grains, bakery),

[11] For the NLS estimation, we used the "nl" command in Stata with predetermined initial values without using grid search. As a robustness check for the NLS estimation of the CES production function, we also run the OLS regression after linearization. The results for both the NLS and OLS regressions are reported in Table D7 in the appendix.

SCTG08 and 09 (beverages and tobacco). Overall, our results confirm that food manufacturing is an input-intensive industry, as depicted in Huang (2003), Gandhi *et al*. (2020) and (Wahdat & Lusk, 2023)).

In addition, our results also consistently display that locally produced and imported inputs are neither substitutes nor complements as indicated by the measured elasticities of substitution equal to one (or substitution parameter θ equal to zero) as indicated by the Wald test of each agricultural commodity in Table D7. We believe that the lack of clear substitution or complementarity between locally grown and imported agricultural inputs is attributable to the fairly large number of commodities associated to each SCTG. For instance, SCTG02 commodities alone include wheat, corn, rye, barley, oats, and rice. As a result, the effect of substituting local corn with imported corn is confounded with substitution for other commodities such as wheat or rice. The same applied to SCTG01 and SCTG03 commodities. These results indicate that while states do not prioritize local over imported inputs and vice versa, both inputs contribute to the production of manufactured food with significantly positive productivity. Robustness check with alternative capital stock measures in Appendix D confirms this result.

4.3 Marginal effect of drought on manufactured food production

We have analyzed the average effect of drought on agricultural trade and the effect of each input aggregate on manufactured food sector. However, it is still unclear where the strongest drought effect comes from. In this section, we graphically present the main trade linkages for the two main agricultural input groups (cereal grains and fruits/vegetables) and the extent to which each input link impacts the production of manufactured food. And all the scenarios quantify the effect of an increase in severe drought ($|SPEI| < -1.3$).[12] The full matrix derivative of manufactured food production, equation (A3) (as is well-known in spatial econometrics literature), constitute three marginal effects – the intrastate, inward, and outward effect. For the sake of brevity, how each effect is represented with the parameter estimates from the main regression analysis will not be discussed here but rather in Appendix A. The first section is pertinent to the marginal effects calculated in the appendix for Illinois and its trading partners.[13] We then give the aggregate effect of a national drought and the aggregate change on the

[12] The maps that illustrate mild drought ($|SPEI| > -1.3$) impacts are available upon request to the authors.
[13] Estimates and standard errors of the marginal effects for other states are available upon request to the authors

manufactured food production at the national level.

4.3.1 Drought and impacts for Illinois

To examine which trade linkages are important for Illinois' manufactured food sector when Illinois faces drought, we first investigate the intrastate effect. This is the change in manufactured food production in Illinois from an increase in Illinois drought. Figure 7 displays the increase in manufactured food production in Illinois for the average simulation years (average of 1997 – 2017) in million US dollars. Panel A depicts that in the face of a 1 percent increase in severe local drought, Illinois relies on cereal grain (SCTG02) imports for inputs in the manufactured food sector from Midwestern states. The compensated production gain in the manufactured food sector mostly come from importing cereal grains from Wisconsin (597.706 million $), Indiana (583.688 million $), Iowa (349.342 million $), Missouri ($286.113 million $), South Dakota (200.561 million $), and Nebraska (127.899 million $). As depicted in panel B, the strongest trade linkages for vegetables, fruits, and other agricultural products (SCTG03) used as inputs for processed food in Illinois is more focused on partners in the Upper Midwest. Again, the highest gain in manufactured food production was from imports that come from Iowa (675.796 million $), Missouri (574.474 million $), Indiana (450.463 million $), Wisconsin (307.371 million $), and Minnesota (112.138 million $). And notably, the trade impact is more far-reaching towards California (87.756 million $ compared to 0.650 million $ for cereal grains), Idaho (51.246 million $ compared to 4.592 million $ for cereal grains), and Texas (83.256 million $ compared to 12.292 million $ for cereal grains). The reliance on these three states for commodity 03 is nearly in proportion to their rankings of vegetables, fruit, tree nut and berry crops sales in 2017.[14] Nevertheless, the fact that Illinois' manufactured food production increased more with commodity 03 inflows from the midwestern states means that there are comparative advantages for products from states that are located close-by with possibly lower transportation costs.

Figure 8 presents the loss in Illinois manufactured food production from trading with states that experience drought. In short, the findings reveal that the loss felt by manufactured food

[14] According to the USDA NASS, 10 states accounted for 79 percent of U.S. vegetables sales in 2017. These states include California which sold 8,167.80 million US$ (42 percent) ranking first, followed by Florida (1,284.10 million US$) and Idaho (1,147.10 million US$). For fruits, tree nut and berry, states covered 95 percent of sales with highest sales from California (19,708 million US$), Washington (3,614.9 million US$), and Florida (1,298.7 million US$). Texas is also one of the top 10 states, accounting with 213.3 million US$ sales in 2017.

production in Illinois is much bigger for inflows of cereal grains (SCTG02) relative to those of commodity 03. Panel A depicts that a 1 percent increase in Wisconsin, Indiana, Missouri, and Iowa leads to a decrease in Illinois manufactured food production due to their associated trade linkages of cereal grains (02). These interregional impacts are especially pronounced for severe drought in Wisconsin (loss of 763.531 million $) and Indiana (loss of 745.625 million $). Panel B reveals that loss of manufactured food sector in Illinois is associated with higher drought experienced in Iowa, Missouri, Indiana, and Wisconsin because Illinois relies on commodity 03 products the most from these states. The most acute impacts are from Iowa and Missouri with respective loss of 123.361 million $ and 104.865 million $.

Figure 9 depicts the loss in destination states' manufactured food production from higher drought in Illinois. As seen in panel A of Figure 9, Illinois drought impacts are mostly concentrated in the Upper Midwest. Indiana experienced the highest loss of 646.692 million $ manufactured food production (1.88 percent of the sector's average total production for 1997 – 2017) as a result of less available cereal grain imports from drought-struck Illinois. Notably, these impacts are not only felt in close-by states but are also far-reaching to the manufactured food sector located in the Ohio Valley and the Southeast. States located in the far south such as Florida, Tennessee, Georgia, and Louisianna also are impacted by Illinois drought. The loss is largest for Florida with 544.377 million $ loss which is about 9.78 percent of total food manufacturing production (55,674.942 million $; 1997 – 2017 average) in Florida. For Tennessee, the loss was 414.302 million $ which is about 11.73 percent of total production of manufactured food sector (35,297.33 million $; 1997 – 2017 average). This means that while Florida and Tennessee are located far south from Illinois, a large proportion of their manufactured food production rely on cereal grain inputs sourced from Illinois, a major U.S. crop producer. Similar to Figure 8, the drought impacts are smaller for commodity 03 inputs (panel B) compared to commodity 02 inputs (panel A) which makes sense since Illinois is not a major producer of commodity 03 products. Nevertheless, there are closely located states (e.g., Missouri, Indiana, and Wisconsin) that are still weakly associated with decreased imports from the drought-hit Illinois.[15]

4.3.2 Drought and impacts at the national level

[15] Here we say weakly associated because the standard errors are high relative to the estimated coefficients for commodity 03 inputs. The estimated effects and standard errors are reported in the Appendix.

Having investigated the drought impacts on food manufacturing production at the state level specifically for Illinois and its crop trading partners, we next analyze the effects at the national level. The first marginal effect is pertinent to the aggregate inward effect which is the sum of the effects from droughts experienced in all the trading states (except for the state itself). Figure 10 illustrates the food manufacturing production loss in the importing state when there is higher drought in the rest of the country. As seen in panel A, the most prominent loss is seen in California amounting to 7,478.246 million $, followed by Texas with 4,307.488 million $ loss. This is attributable to decreased inflow of cereal grains from all the other states (potential exporters) that have less available stocks to export as they face severe drought. Such decrease in food manufacturing production for California and Texas is in commensurate with the total production of food manufacturing (see Figure 3). This means that high manufactured food producing states rely on cereal grain inputs from other states and therefore their food sector is more sensitive to drought happening in other locations. Notably, some states in the Northeast (e.g., New York and Pennsylvania) also experience sizable production loss, with decreases of 3,097.573 million $ and 2,838.982 million $, respectively, through cereal grain imports. For these states, the loss is large given that they are large producers of manufactured food but also mainly because they rely heavily on cereal grain imports from other states to use as necessary inputs. For panel B, the national drought impacts due to decreased commodity 03 imports are smaller (and less statistically significant) compared to the loss induced from less commodity 02 input inflows. This indicates that the state-level processed food sector relies more strongly on cereal grains produced in other states as opposed to imported vegetables, fruits, and other agricultural products (SCTG03).

Figure 11 presents the sum of drought impacts on food manufacturing production through exports of commodity 02 (panel A) and 03 (panel B). The most acute loss in national production was from severe drought in Nebraska, Indiana, and Illinois with *aggregate* losses of 7,132.734 million, 5,957.264 million, and 5,097.156 million US$, respectively (as seen in panel A). And importantly, the map reveals that the national production is most sensitive to droughts in the midwestern states. Conversely, the aggregate loss through decreased exports of commodity 03 is less pronounced overall and more dispersed (as seen in panel B). The key implication of this finding is that the substantial loss of national food manufacturing production is attributable to decreased cereal grain exports, especially from states located in the Northern Rockies and Plains, Upper Midwest and the Ohio Valley. This is also a strong implication that these cereal grain exporters are responsible for the majority of these inputs sourced to be used for manufactured food production. Thus, the U.S. food system would be especially susceptible to drought concentrated in the Midwest, such as the drought that hit a majority of midwestern states in 2012. This adds support to the notion that crop trade linkages can have profound implications for the national food supply chain in the face of future extreme weather events.

5 Conclusion

Growing population and the increasing occurrence of extreme weather events oblige us to investigate further the impact of a changing climate on the food supply chain in the United States. This paper proposes to tackle this crucial relationship through a novel two-stage approach that allows us to include both interstate and intersectoral spillovers and deal with their endogeneity in the determination of food manufacturing production. Food manufacturing per se is an indoor activity, hence it is not directly affected by extreme events such as drought; however, its inputs - agricultural commodities grown either locally or in other states - certainly are. In the first stage, we consider the variation in the volume of exported agricultural commodities due to extreme weather in the frame of a gravity model of trade. We then apply a nested Cobb-Douglas production function to identify the effect of labor, capital as well as of local and imported agricultural inputs on the manufacturing of food. The results display three main findings. First, we confirm that drought in the exporting state decreases the exports of cereal grains (SCTG02) and of other agricultural products (SCTG03). Inversely, drought in the destination states obliges them to increase imports as they need to carry on with their manufacturing activities and previous year's storage does not always suffice. Therefore, the interstate agricultural supply chain mitigates the impact of weather extremes on food availability. Second, stage 2 results confirm that productivity of both capital and labor is positive and larger for labor, hence indicating that food manufacturing is a labor-intensive industry. Third, states do not treat local and imported inputs as substitutes. Instead, all agricultural commodities are necessary inputs in the food manufacturing process.

Overall, the results of this study provide us with a better understanding of how to maintain the nation's long-run ability to cope with shifts in the food supply chain from climate shocks while pursuing the challenge of feeding a growing population. Moreover, the study's findings provide details on the key linkages in the domestic food supply chain and are informative for the design of policies aiming at mitigating the impacts of climate change on the U.S. food and agricultural sector. Future extensions will focus on providing results by transportation mode and by commodity, even though the latter approach would require crop-specific supply chain data to be created. Another venue of research is the inclusion of other extreme weather events (e.g., early frost, heavy rainfall) as well as providing projections based on climate conditions by the end of the century.

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Tables and Figures

Table 1: Distributional weights of SCTG01-03 inputs to SCTG04-09

A. Before rescaling

	SCTG									Household demand	Export	Sum
	01	02	03	04	05	06	07	08	09			
01	0.109	0.002	0.003	0.000	0.574	0.007	0.193	0.000	0.000	0.056	0.001	0.767
02	0.082	0.031	0.004	0.137	0.000	0.355	0.052	0.035	0.000	0.019	0.174	0.579
03	0.005	0.004	0.059	0.000	0.000	0.022	0.315	0.014	0.000	0.262	0.203	0.337

B. After rescaling to include only SCTG04-09 and weights above 2 percent

	SCTG						Sum
	04	05	06	07	08	09	
01		0.749		0.251			1.000
02	0.237		0.613	0.089	0.061		1.000
03			0.066	0.934			1.000

Table 2: Description of the variables in the gravity model

Variable	Description	Source
Trade flows of agricultural commodity ***k***	Volume of ***k*** traded between the origin and destination state (1,000 tons)	FAF
Drought	Absolute value of SPEI for all SPEI < 0 in the origin and destination state	ERA5-Land
Wetness	Value of SPEI > 0 for all SPEI > 0 in the origin and destination state	ERA5-Land
Ag. GDP	Total output of agricultural commodity ***k*** in the origin state (2012 U.S.$)	FAF
Food GDP	GDP of food, beverages and tobacco manufacturing industry in the destination state (2012 U.S.$)	BEA
Growing degree days	Temperature as measured in growing degree days during the growing season in farmland	ERA5-Land
Precipitation	Precipitation during the growing season in farmland (m)	ERA5-Land
Population	Total population of destination state	BEA
Distance	Travel time between origin and destination state	OSRM
Contiguity dummy	Dummy variable equal to 1 if origin and destination states are sharing a border	
Home dummy	Dummy variable equal to 1 for within-state flows	

Table 3: Description of the variables in the production function

Variable	Description	Source
Output of processed food	Sum of total traded processed food products (SCTG04-09) leaving the state representing total output of manufactured food in 2012 USD	FAF
Labor	Total full- and part- time employment (or number of jobs) for the food, beverages, and tobacco manufacturing industry	BEA
Capital	National capital stock for the food, beverages, and tobacco manufacturing industry in 2012 US Dollars allocated by share of state GDP	FRB, BEA
Local SCTG01	Predicted intrastate trade flow of animals and fish (SCTG01)	Gravity model
Imported SCTG01	Sum of all predicted interstate flows of animals and fish (SCTG01)	Gravity model
Local SCTG02	Predicted intrastate trade flow of cereal grains (SCTG02)	Gravity model
Imported SCTG02	Sum of all predicted interstate flows of cereal grains (SCTG02)	Gravity model
Local SCTG03	Predicted intrastate trade flow of other agricultural products (SCTG03)	Gravity model
Imported SCTG03	Sum of all predicted interstate flows of other agricultural products (SCTG03)	Gravity model

Table 4: Gravity model estimates

	Animals and Fish (01)		Cereal Grains (02)		Vegetables, Fruits, and Other (03)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Drought_home ($i = j$)	0.307	(0.306)	0.260	(0.179)	-0.127	(0.146)
Drought_orig. ($i \neq j$)	0.048	(0.533)	-0.531**	(0.264)	-0.056	(0.320)
Drought_dest. ($j \neq i$)	-0.628	(0.510)	0.464*	(0.289)	0.466	(0.302)
Wetness_home ($i = j$)	0.047	(0.348)	-0.002	(0.141)	0.127	(0.161)
Wetness_orig. ($i \neq j$)	-0.107	(0.626)	0.407	(0.458)	-0.331	(0.262)
Wetness_dest. ($j \neq i$)	1.792**	(0.707)	0.197	(0.317)	0.351	(0.248)
Ag GDP_orig.	0.747***	(0.115)	0.592***	(0.086)	0.448***	(0.068)
L_Food GDP_dest.	-0.161	(0.178)	-0.059	(0.181)	0.063	(0.150)
GDD_home ($i = j$)	0.110	(0.893)	0.216	(0.885)	0.262	(0.674)
GDD_orig. ($i \neq j$)	-1.366	(1.658)	0.302	(1.545)	-0.308	(1.417)
GDD_dest. ($j \neq i$)	6.701***	(1.658)	-1.986*	(1.168)	0.193	(1.642)
Precipitation_home ($i = j$)	0.052	(0.389)	0.385	(0.255)	-0.111	(0.135)
Precipitation_orig. ($i \neq j$)	0.072	(0.713)	-0.434	(0.407)	0.106	(0.235)
Precipitation_dest. ($j \neq i$)	-0.802	(0.648)	-0.060	(0.392)	0.203	(0.247)
Population_dest.	-1.631*	(0.958)	1.116	(0.815)	0.548	(0.577)
Pseudo R-squared	0.963		0.965		0.970	
Observations	5,680		7,555		10,940	

Note: Standard errors are clustered by state pairs and are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. All estimations include state-pair, exporter climate zone-year, and importer climate zone-year fixed effects. MRTs for distance, neighbor and home dummy are also included for all estimations. Constant was included in the analysis but not reported in this table. GDD is growing degree days.

Table 5: Gravity model estimates with extreme and mild drought

	Animals and Fish (01)		Cereal Grains (02)		Vegetables, Fruits, and Other (03)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Extreme drought_home ($i = j$)	0.241	(0.312)	0.225	(0.183)	-0.152	(0.143)
Mild drought_home ($i = j$)	0.319	(0.305)	0.241	(0.176)	-0.089	(0.150)
Extreme drought_orig. ($i \neq j$)	-0.273	(0.536)	-0.753**	(0.323)	-0.119	(0.317)
Mild drought_orig. ($i \neq j$)	0.127	(0.545)	-0.454	(0.311)	-0.129	(0.331)
Extreme drought_dest. ($j \neq i$)	-0.039	(0.568)	0.590*	(0.346)	0.652**	(0.301)
Mild drought_dest. ($j \neq i$)	-0.700	(0.511)	0.494*	(0.298)	0.343	(0.320)
Wetness_home ($i = j$)	0.049	(0.342)	-0.001	(0.143)	0.152	(0.167)
Wetness_orig. ($i \neq j$)	-0.182	(0.650)	0.465	(0.466)	-0.365	(0.268)
Wetness_dest. ($j \neq i$)	1.720**	(0.725)	0.219	(0.292)	0.260	(0.237)
Ag GDP_orig.	0.746***	(0.115)	0.590***	(0.086)	0.448***	(0.068)
L_Food GDP_dest.	-0.163	(0.178)	-0.055	(0.184)	0.059	(0.153)
GDD_home ($i = j$)	0.130	(0.929)	0.217	(0.898)	0.241	(0.675)
GDD_orig. ($i \neq j$)	-1.149	(1.682)	0.202	(1.532)	-0.301	(1.406)
GDD_dest. ($j \neq i$)	6.328***	(1.676)	-1.908*	(1.151)	0.324	(1.650)
Precipitation_home ($i = j$)	0.074	(0.380)	0.370	(0.255)	-0.119	(0.133)
Precipitation_orig. ($i \neq j$)	0.222	(0.707)	-0.482	(0.402)	0.103	(0.239)
Precipitation_dest. ($j \neq i$)	-0.807	(0.660)	-0.036	(0.375)	0.241	(0.240)
Population_dest.	-1.657*	(0.974)	1.130	(0.826)	0.529	(0.577)
Pseudo R-squared	0.963		0.965		0.973	
Observations	5,680		7,555		10,940	

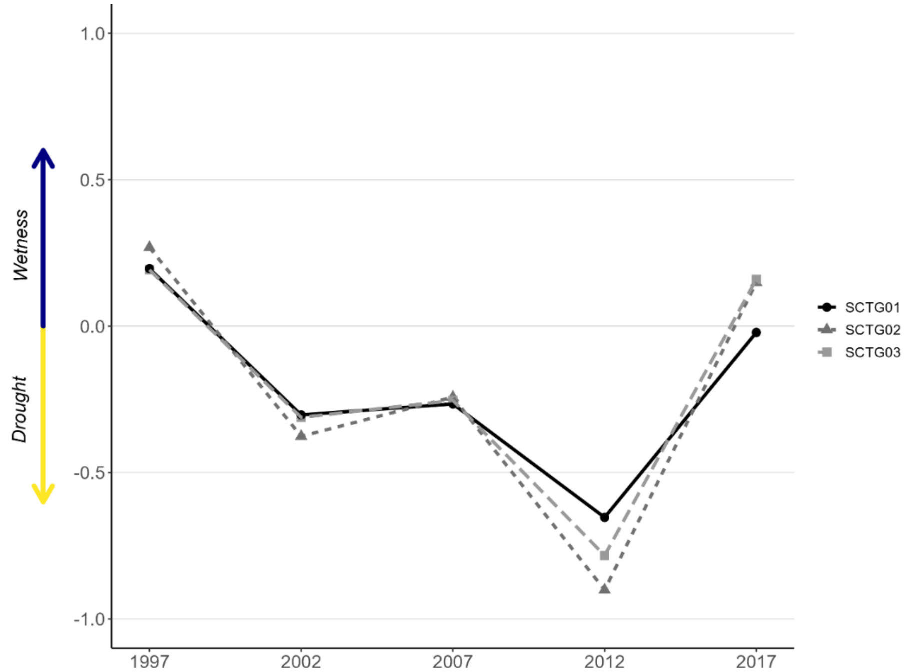
Note: Standard errors are clustered by state pairs and are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. All estimations include state-pair, exporter climate zone-year, and importer climate zone-year fixed effects. MRTs for distance, neighbor and home dummy are also included for all estimations. Constant was included in the analysis but not reported in this table. GDD is growing degree days.

Table 6: Production function estimates

	(1) With extreme/mild drought		(2) Without extreme/mild drought	
	Coefficient	Std. Error	Coefficient	Std. Error
Capital	0.195**	(0.082)	0.196**	(0.082)
Labor	0.590***	(0.100)	0.594***	(0.100)
Animals and Fish (01)	-0.006	(0.016)	-0.005	(0.016)
Cereal Grains (02)	0.057***	(0.021)	0.057***	(0.021)
Vegetables, Fruits, and Other (03)	0.056+	(0.037)	0.054+	(0.037)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	240	240	240	240

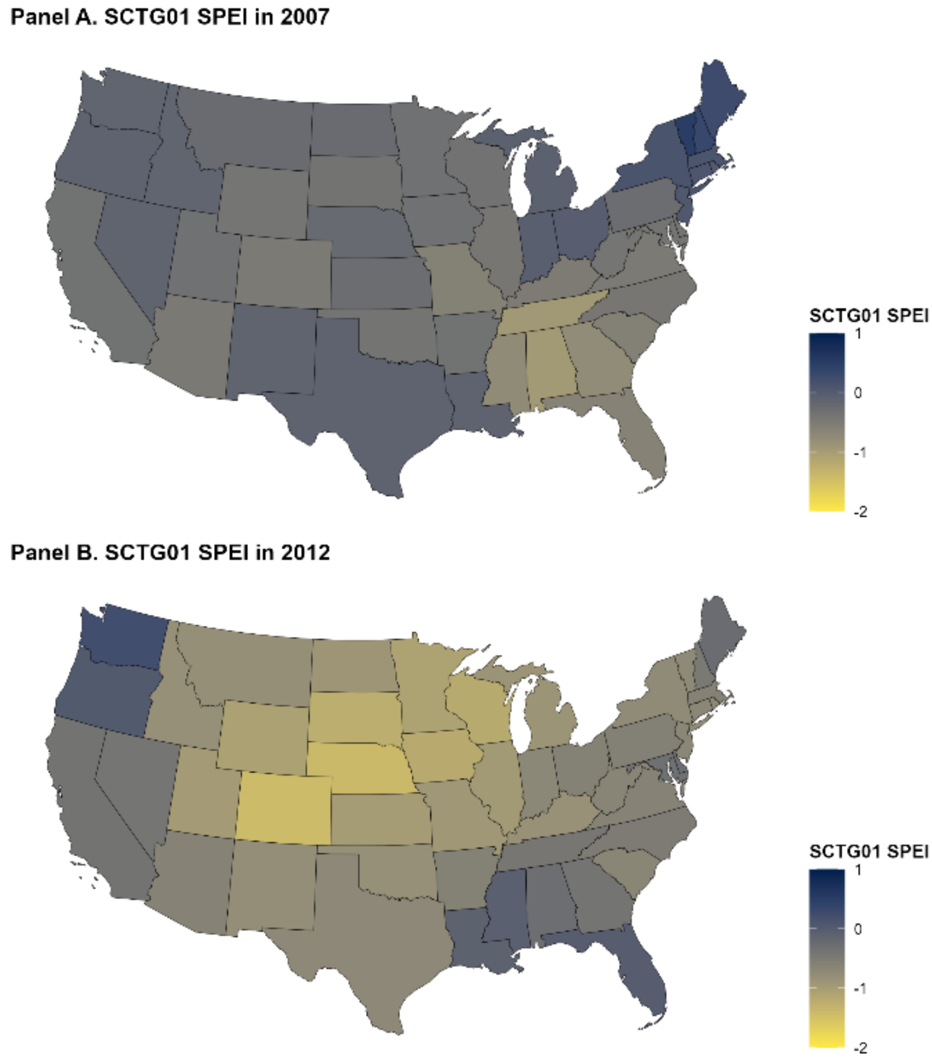
Note: Standard errors are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *, $p < 0.15$ +. Column 1 shows coefficients that are from including agricultural input variables estimated from the gravity model (stage 1) with extreme and mild drought conditions. Column 2 shows results when including agricultural input variables estimated with drought conditions that are not divided into extreme or mild. The estimates are from regression with constraints where output elasticities of locally produced and imported inputs are the same. They are equivalent to the marginal effects from the nonlinear estimation of the production function with CES input aggregates (as explained in Appendix A). The output elasticity of labor is the estimate from the linear combination of parameters $1 - \beta - \gamma_1 - \gamma_2 - \gamma_3$.

Figure 1: Trend in the annual SPEI of the United States, 1997 – 2017



Notes: The index at the national level is calculated by taking the average of the state-level SPEIs for each agricultural commodity (01 – 03). Negative (or positive) SPEI indicates drought (or wetness).

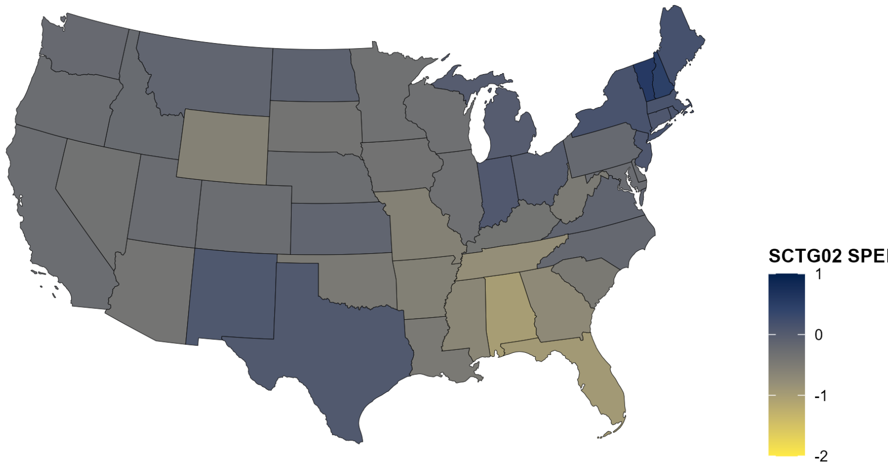
Figure 2A: SPEI for Animals and Fish (SCTG01) commodity across states, 2007 and 2012



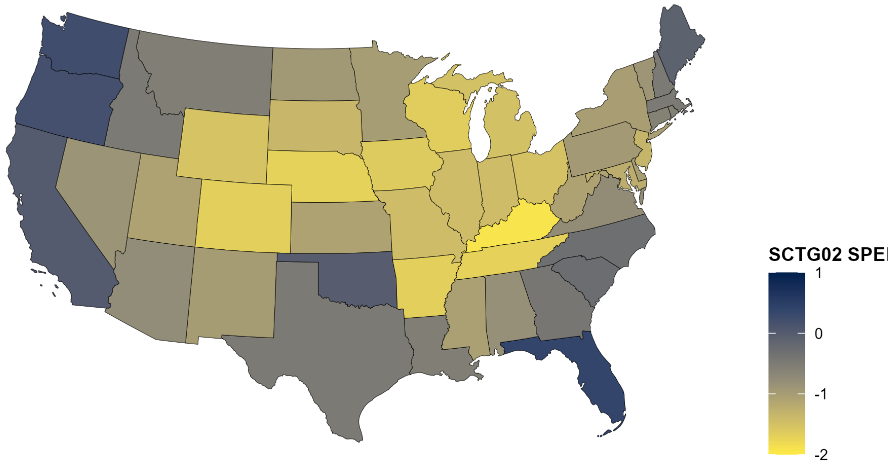
Notes: The map shows the annual state-level SPEIs for commodity 01 for the years 2007 (Panel A) and 2012 (Panel B). The index ranges from -2 to 1 in our sample of 48 states. Negative (yellow) SPEI indicates drought, and positive (navy) SPEI indicates wetness.

Figure 2B: SPEI for Cereal Grains (SCTG02) commodity across states, 2007 and 2012

Panel A. SCTG02 SPEI in 2007

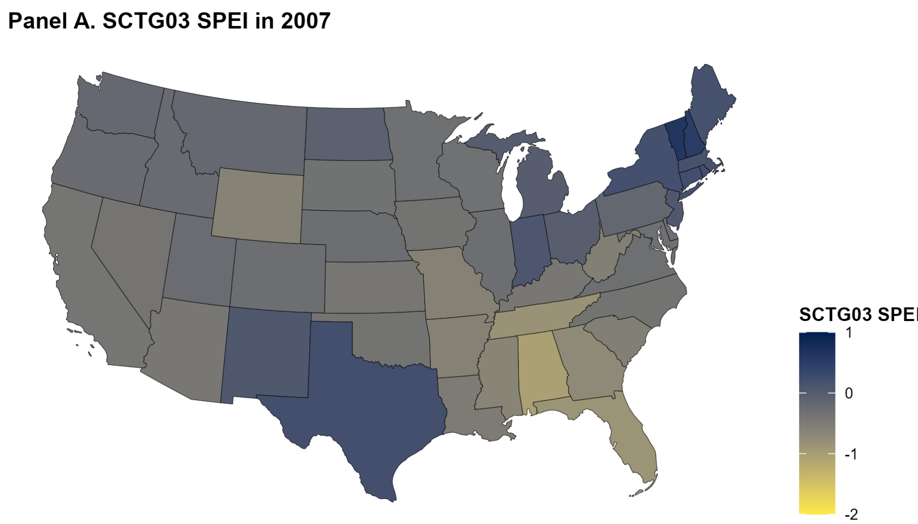


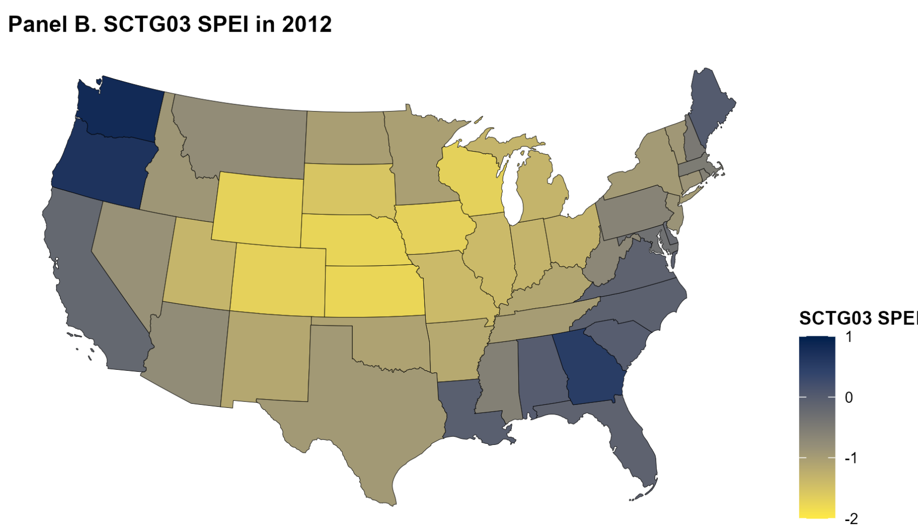
Panel B. SCTG02 SPEI in 2012



Notes: The map shows the annual state-level SPEIs for commodity 02 for the years 2007 (Panel A) and 2012 (Panel B). The index ranges from -2 to 1 in our sample of 48 states. Negative (yellow) SPEI indicates drought, and positive (navy) SPEI indicates wetness. Negative SPEIs were observed for 44 states, and 21 of these states recorded lower than -1 SPEIs.

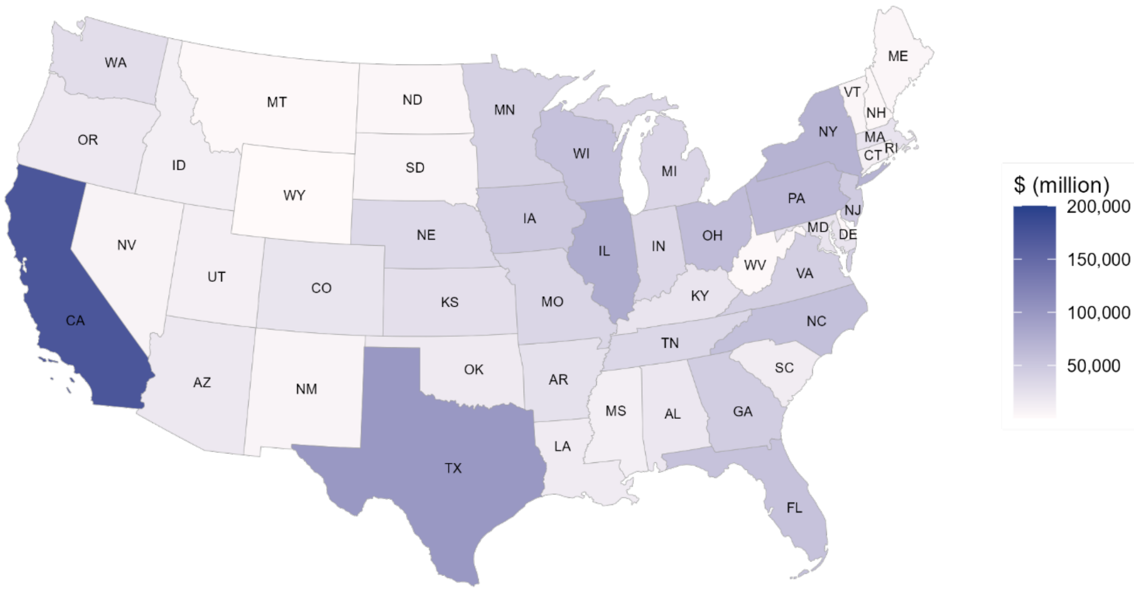
Figure 2C: SPEI for Vegetables, Fruits and Other Agricultural Products (SCTG03) commodity across states, 2007 and 2012





Notes: The map shows the annual state-level SPEIs for commodity 03 for the years 2007 (Panel A) and 2012 (Panel B). The index ranges from -2 to 1 in our sample of 48 states. Negative (yellow) SPEI indicates drought, and positive (navy) SPEI indicates wetness.

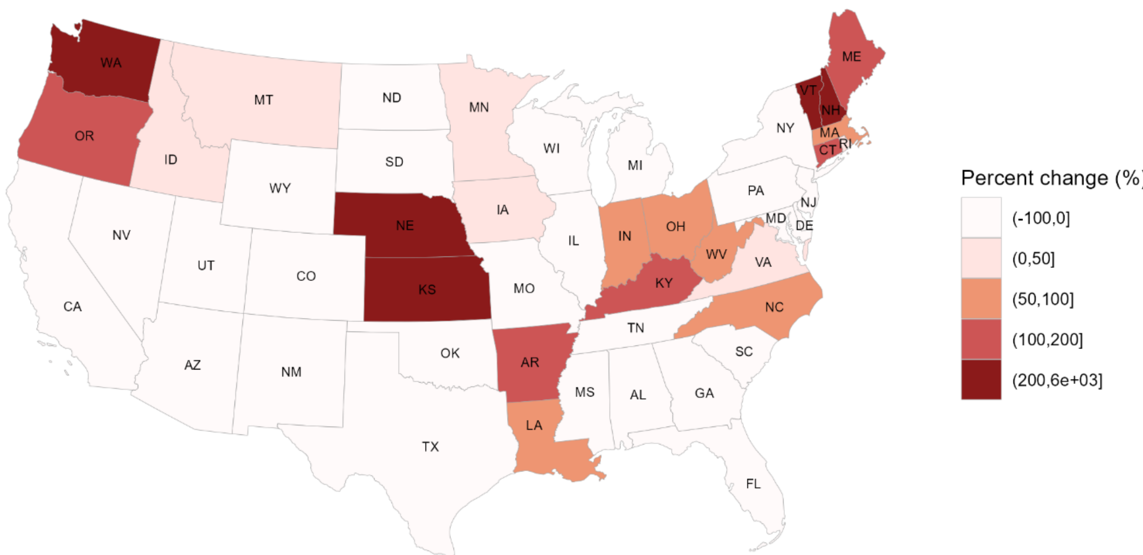
Figure 3: Total production of manufactured food, as average 1997 - 2017



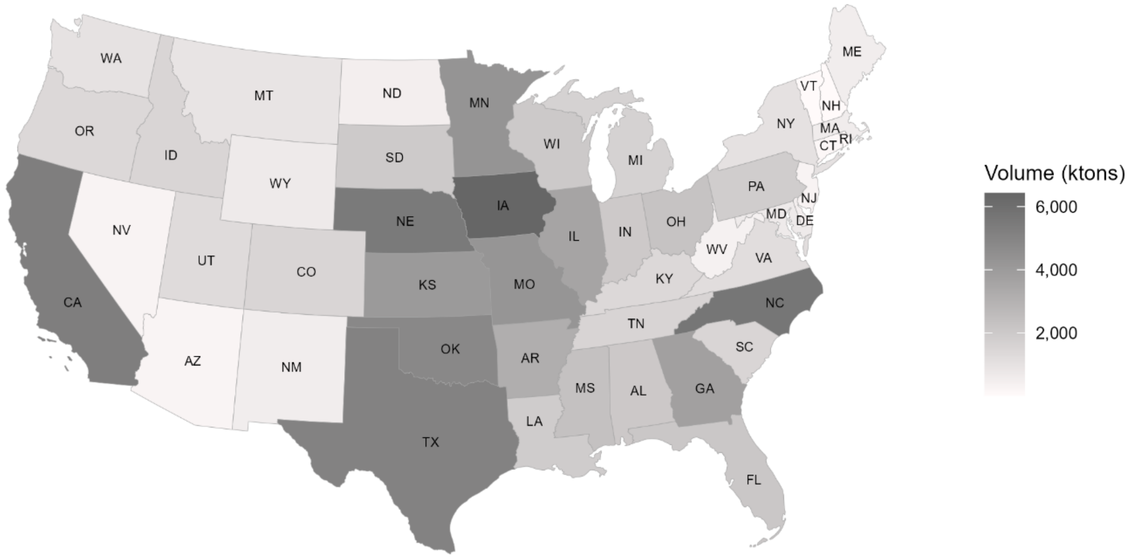
Notes: The map shows the average of the annual production of manufactured food for the five years between 1997 – 2017. Total production is calculated as the sum of all the outflows of the agri-food commodities 04 – 09 for each state. All the values are in 2012 constant dollars.

Figure 4: Import ratio and total production of Animals and Fish (SCTG01)

A. Import ratio, as percent change 2007 - 2012



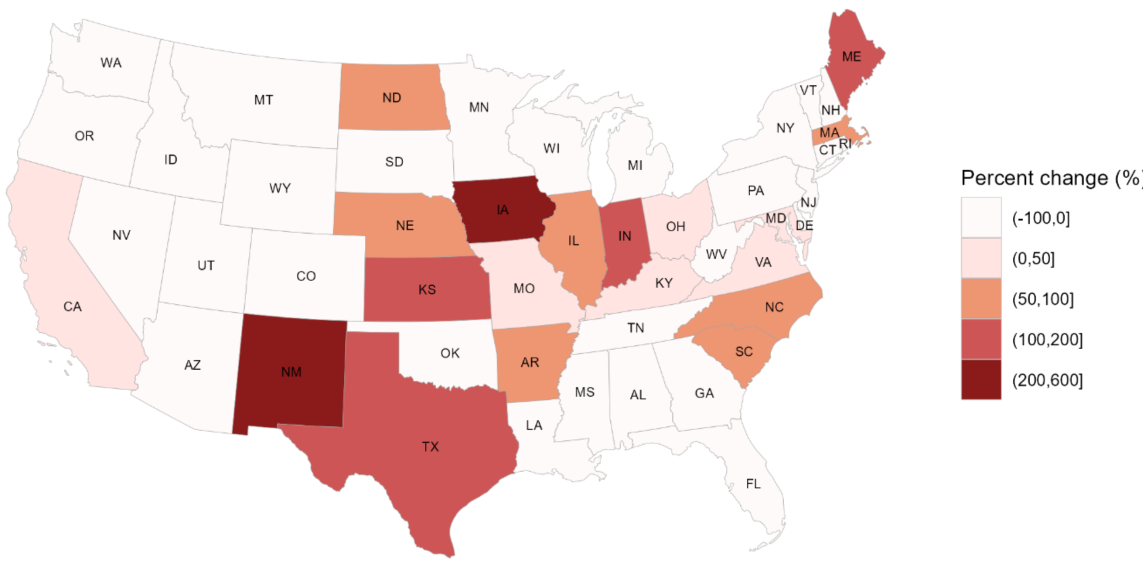
B. Total production, as average 1997 - 2017



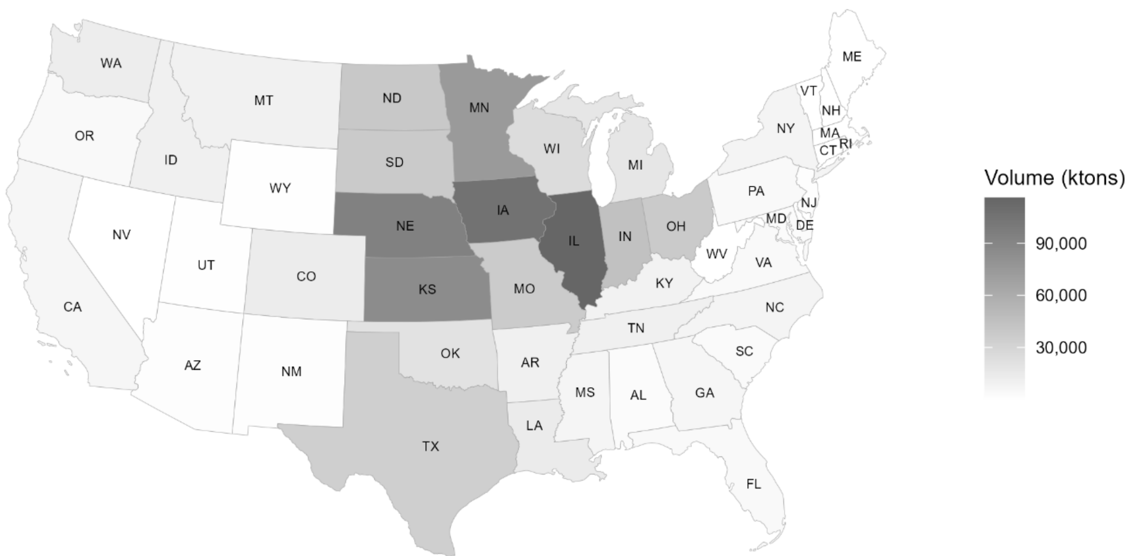
Notes: Panel A shows the percentage change of import ratio from 2007 to 2012. Import ratio is calculated as the imported amount per 1 kilo tons of locally produced commodity 01. Panel B shows the total production of commodity 01 as the average of the annual values for 1997 – 2017. Total production is aggregated as the sum of all domestic outflows of commodity 01.

Figure 5: Import ratio and total production of Cereal Grains (SCTG02)

A. Import ratio, as percent change 2007 - 2012



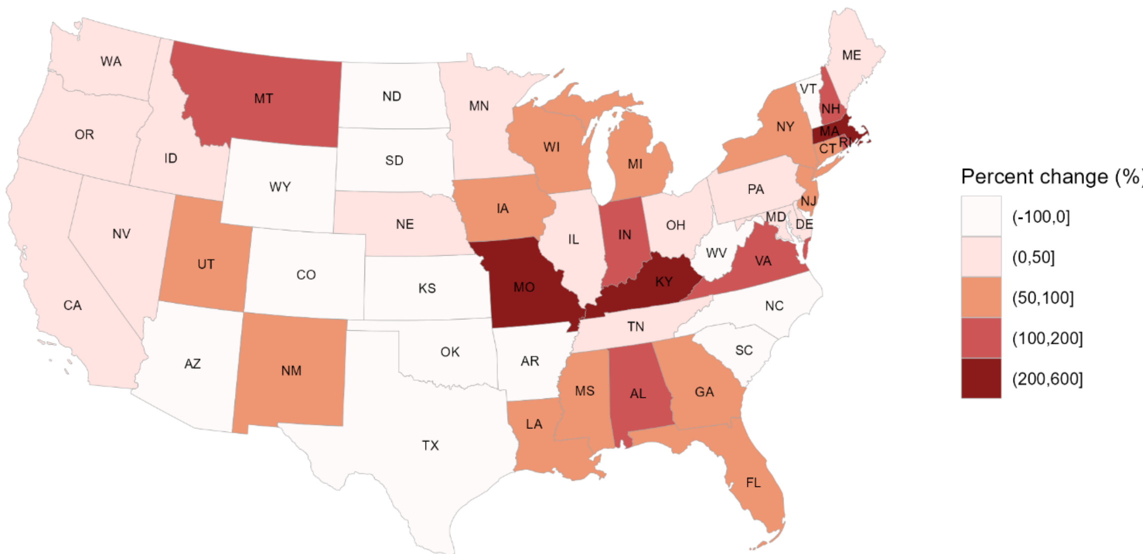
B. Total production, as average 1997 - 2017



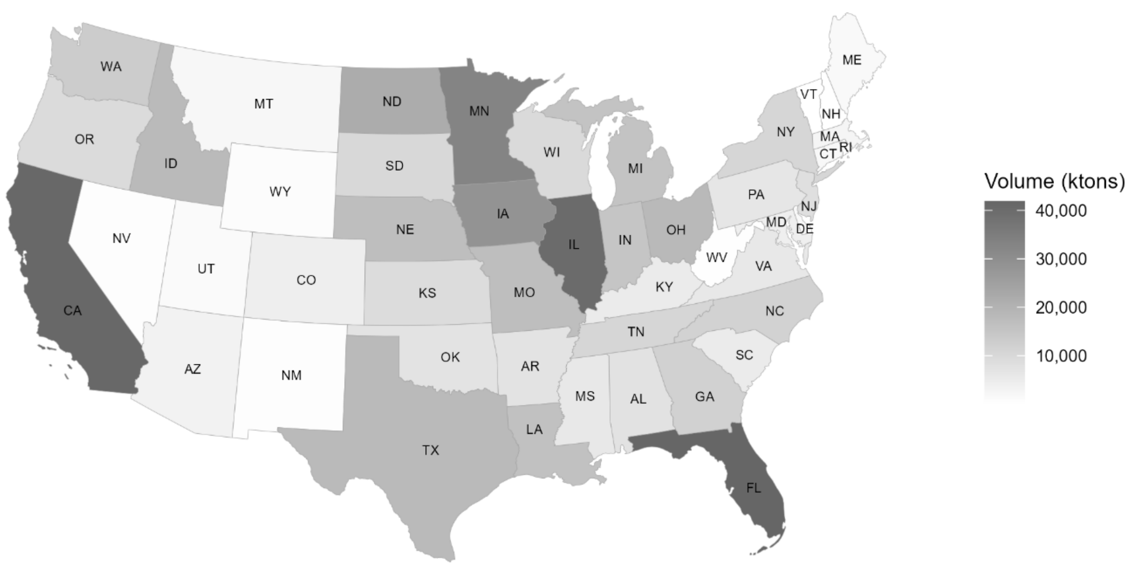
Notes: Panel A shows the percentage change of import ratio from 2007 to 2012. Import ratio is calculated as the imported amount per 1 kilo tons of locally produced commodity 02. Panel B shows the total production of commodity 01 as the average of the annual values for 1997 – 2017. Total production is aggregated as the sum of all domestic outflows of commodity 02.

Figure 6: Import ratio and total production of Vegetables, Fruits, and Other Agricultural Products (SCTG03)

A. Import ratio, as percent change 2007 - 2012



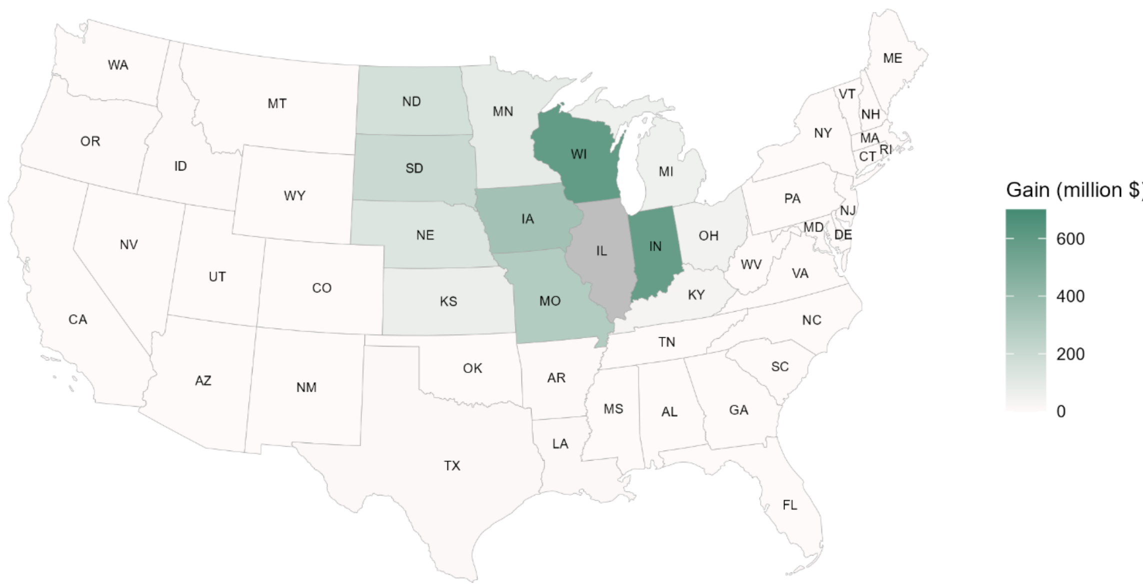
B. Total production, as average 1997 - 2017



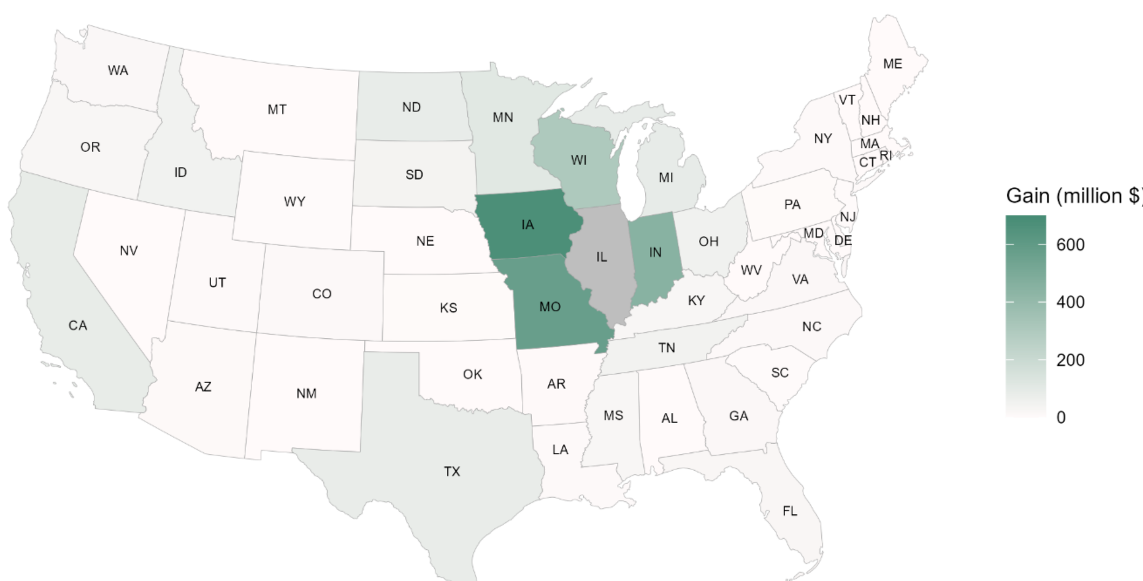
Notes: Panel A shows the percentage change of import ratio from 2007 to 2012. Import ratio is calculated as the imported amount per 1 kilo tons of locally produced commodity 03. Panel B shows the total production of commodity 01 as the average of the annual values for 1997 – 2017. Total production is aggregated as the sum of all domestic outflows of commodity 03.

Figure 7: Gain in IL food manufacturing production following a 1 percent drought increase in IL (gray) with imported inputs from the State of origin (colored)

A. Cereal Grains (SCTG02)



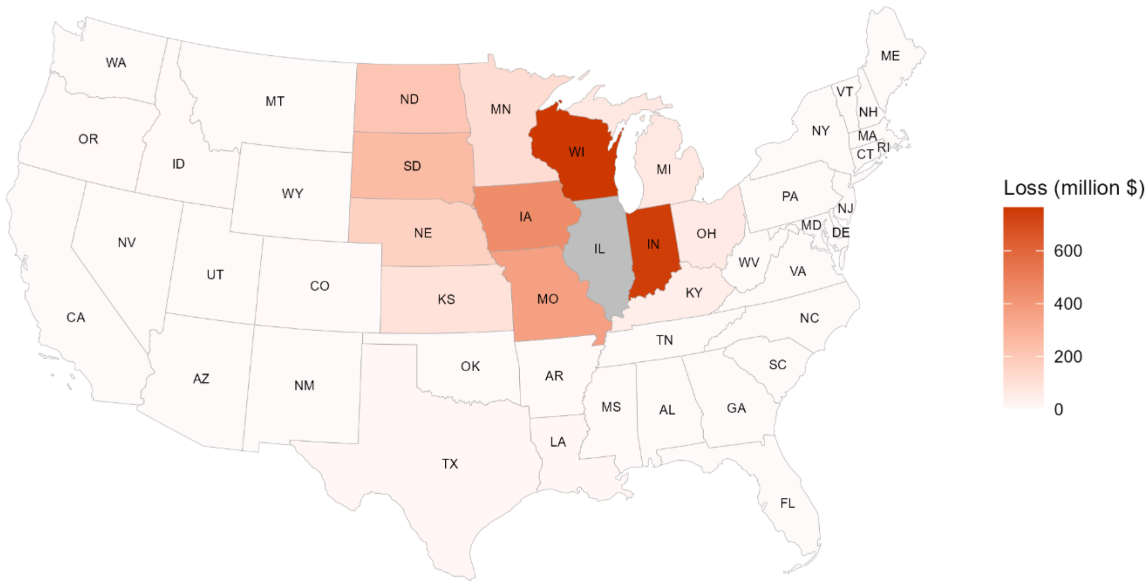
B. Vegetables, Fruits, and Other Agricultural Products (SCTG03)



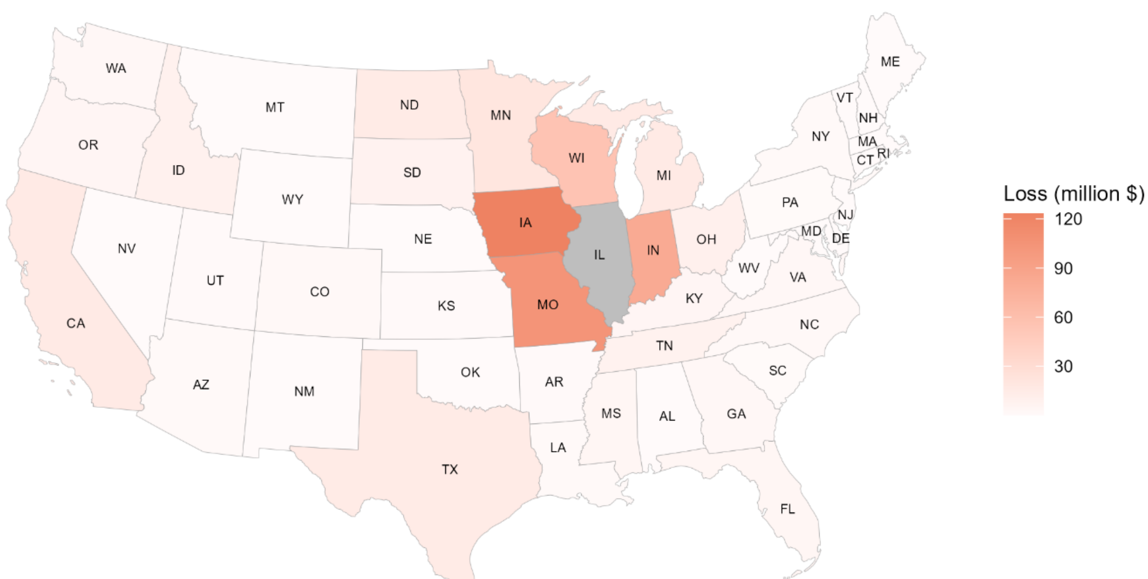
Notes: The figure shows gain in manufactured food production for Illinois from importing the two crop commodities. Each impact is estimated as $\frac{\gamma_k}{2} \cdot \alpha_{jk} \cdot \frac{I_{i,IL,k}}{M_{IL,k}} \cdot Y_j$ . . Estimates and standard errors are reported in Appendix E.

Figure 8: Loss in IL food manufacturing production following a 1 percent drought increase in the State of origin (colored)

A. Cereal Grains (SCTG02)



B. Vegetables, Fruits, and Other Agricultural Products (SCTG03)



Notes: The figure shows loss in manufactured food production for Illinois from importing the two crop commodities from each origin state. Each impact is calculated as $\frac{\gamma_k}{2} \cdot \alpha_{ik} \cdot \frac{I_{i,IL,k}}{M_{IL,k}} \cdot Y_j$ . . Estimates and standard errors are reported in Appendix E.

Appendix A: Marginal Effects of Drought on Manufactured Food Production

Assuming one input group as in equation (A1), the marginal effect (or output elasticity) of local input I on food production Y is (A2):

$$Y = AL^{(1-\beta-\theta)}K^{\beta}\left(\left[I^{\theta}+M^{\theta}\right]^{\frac{1}{\theta}}\right)^{\gamma} \qquad (A1)$$

$$\frac{dlnY}{dlnI} = (1-\beta-\gamma)\cdot\frac{dlnL}{dlnI} + \beta\cdot\frac{dlnK}{dlnI} + \gamma\cdot\frac{I^{\theta}}{I^{\theta}+M^{\theta}} + \gamma\cdot\frac{M^{\theta}}{I^{\theta}+M^{\theta}}\frac{dlnM}{dlnI} \qquad (A2)$$

In (A2), L is labor, I is locally grown inputs, M is imported inputs, β is the output elasticity of capital, γ is the output elasticity of the input group, and θ is the substitution parameter. With $\frac{dlnL}{dlnI}=0$, $\frac{dlnK}{dlnI}=0$, and $\theta=0$ (as estimated in OLS and NLS regression), the direct marginal effect is $\frac{\gamma}{2}$. If we account for indirect effect through change in imported inputs ($\frac{dlnM}{dlnI}$), we also include the fourth term as marginal effect of local input. Elasticity of substitution (σ) is the change in the ratio of inputs with respect to the change in the marginal rate of technical substitution (MRTS). So the elasticity of substitution, σ, is not the same as $\frac{dlnM}{dlnI}$, but since $\sigma=1$, we assume that $\frac{dlnM}{dlnI}=0$. We will report the (direct) marginal effect for now.

Equation (A2) is the marginal effect of input aggregate on manufactured food production which constitutes only the second stage of our analysis. We need the derivative of drought (our exogenous extreme weather shock) on manufactured food production. Equation (A3) is the full matrix derivative of manufactured food production. The diagonal elements are the intrastate effects and is expressed as equation (A4). The first term of equation (A4) is the change in manufactured food production through changes in locally produced input, I_{jk}, called the *local input channel*. The second term will be the same change in manufactured food production Y_j that occur through changes of imported inputs, M_{jk} , which we refer to as the *import input channel*. Equation (A5) represents the effect with our evaluated estimates from the main analysis, where $\sum_{j\neq i}^{48} I_{ik} = M_{jk}$ and the ratio of each trade flow (from $i\ to\ j$) out of imported inputs for state j is $\frac{I_{ijk}}{M_{jk}}$. The trade flow ratio will equal to 1 once summed up across all the trading states which state j imports from that leaves us with (A6). The parameter γ_k is the output elasticity of aggregate input k which is divided into two for each input channel to reflect the no-substitution effect as tests could not reject that the parameter is not significantly different from zero.

$$\frac{\partial \boldsymbol{lnY}}{\partial \boldsymbol{lnD_k}} = \begin{bmatrix} \frac{\partial lnY_1}{\partial lnD_{1,k}} & \cdots & \frac{\partial lnY_1}{\partial lnD_{n,k}} \\ \vdots & \ddots & \vdots \\ \frac{\partial lnY_n}{\partial lnD_{1,k}} & \cdots & \frac{\partial lnY_n}{\partial lnD_{n,k}} \end{bmatrix} \tag{A3}$$

$$\frac{\partial lnY_j}{\partial lnD_{jk}} = \frac{\partial lnY_j}{\partial lnI_{jk}}\frac{\partial lnI_{jk}}{\partial lnD_{jk}} + \frac{\partial lnY_j}{\partial \ln M_{jk}}\frac{\partial \ln M_{jk}}{\partial lnD_{jk}} \tag{A4}$$

$$\frac{\partial lnY_j}{\partial lnD_{jk}} = \frac{\gamma_k}{2}\cdot \alpha_{i=j,k} + \frac{\gamma_k}{2}\cdot \alpha_{jk}\sum_{i\neq j}^{n}\frac{I_{ijk}}{M_{jk}} \tag{A5}$$

$$\frac{\partial lnY_j}{\partial lnD_{jk}} = \frac{\gamma_k}{2}\cdot \alpha_{i=j,k} + \frac{\gamma_k}{2}\cdot \alpha_{jk} \tag{A6}$$

The inward effect is the change in manufactured food production induced from increase in drought in other trading states of origin. These are the off-diagonal row elements of the derivative matrix (A3). In (A7), the local channel for the inward effect ($\frac{\partial lnY_j}{\partial lnI_{jk}}\frac{\partial lnI_{jk}}{\partial lnD_{ik}}$) pertains to increase/decrease in locally produced agricultural inputs induced from drought in other trading states that can occur through changes in multilateral resistance components. This term is equal to zero here since it is beyond the scope of this research where we only evaluate the first-order drought impact on trading states' size terms rather than the multilateral terms from the gravity model. The inward effect is thus represented as (A8) with the evaluated estimates. The aggregate inward effect, or the change in manufactured food production from national drought (or the row sum of the matrix exempt the local drought) is represented as (A9). Here, the sum of the trade flow ratio is also equal to one leaving us with marginal effects as (A10).

$$\frac{\partial lnY_j}{\partial lnD_{ik}} = \frac{\partial lnY_j}{\partial lnI_{jk}} \frac{\partial lnI_{jk}}{\partial lnD_{ik}} + \frac{\partial lnY_j}{\partial \ln M_{jk}} \frac{\partial \ln M_{jk}}{\partial lnD_{ik}} \tag{A7}$$

$$\frac{\partial lnY_j}{\partial lnD_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_{ik} \cdot \frac{I_{ijk}}{M_{jk}} \tag{A8}$$

$$\sum_i^n \frac{\partial lnY_j}{\partial lnD_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_{ik} \sum_i^n \frac{I_{ijk}}{M_{jk}} \quad \forall\, i \neq j \tag{A9}$$

$$\sum_i^n \frac{\partial lnY_j}{\partial lnD_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_{ik} \quad \forall\, i \neq j \tag{A10}$$

The outward effect, or the impact of local drought on all other states of destination, is the same as (A7) only with the $i\ and\ j$ reversed. The aggregate outward effect is the column sum of the derivative matrix (A3), exempt the impact on local production, is represented as (A11).

$$\sum_i^n \frac{\partial lnY_i}{\partial lnD_{jk}} = \frac{\gamma_k}{2} \cdot \alpha_{jk} \sum_i^n \frac{I_{jik}}{M_{ik}} \quad \forall\, i \neq j \tag{A11}$$

Appendix B: Construction of the Weather Data

B.1 Weather variables

We use an extensive dataset on weather variables covering all the areas across the United States from 1981 to 2019. We obtain weather data from the ERA5- Land (Muñoz Sabater, 2021) database which provides daily or monthly weather data at a spatial resolution of 4km. This data is used to aggregate pixel readings to the county level by averaging across pixel observations located within the county. Then we compute two weights with respect to time and space in order to aggregate county-level drought index to the state-level for each of the five years in our study period (1997, 2002, 2007, 2012, 2017). We obtain data on Standardized Precipitation Evapotranspiration Index (SPEI) which is provided as monthly observations. Other aggregated county-level weather variables are daily Growing Degree Days (GDD) and daily precipitation.

B.2 Weighing scheme

Since our study concerns the planting and harvesting of crops and growth of livestock at the state level, we need state-level yearly measurements that is more sector-specific than simple averages by year and by state. We use the 2017 farmland and planting/harvesting period information in two ways. First, we define the growing season as the weighted average of the middle date of the planting period (as the start date of the growing season) and the harvesting period (as the end date of the growing season) of all the products within the SCTG02 and SCTG03 categories. This addresses the issue that planting, harvesting and growing periods are not uniform across commodities. For instance, SCTG02 contains crops such as wheat, corn, barley and rice for which the planting and harvesting periods all differ by state. The weights will be based on the farmland area of each product in SCTG02 from the USDA FSA (USDA, 2022). Planting and harvesting periods of each product in SCTG02/SCTG03 are provided by state in the USDA NASS database (USDA, 2022). Livestock products are also likely to be related to extreme weather events resulting from change of climate but are less dependent on the seasons, thus we assume that livestock is produced throughout the year.

Next, we aggregate county-level weather observations to the state-level based on the farmland area of each county. We sum farmland acreage of each product included in SCTG02/SCTG03 for each county from the USDA FSA. The weights for each county are calculated as the ratio of the total area used to grow SCTG02 products to the total area of the state. For SCTG01, we use information from USDA NAAS Census of Agriculture on county-level total sales of each live product for the aggregation of county-level observations to state-level measures (USDA, 2022).

Appendix C: Construction of Labor Data

For some states, the undisclosed value is the only on missing observation so we can easily recover it as the difference between the upper region the state belongs to and the sum of the other states in that region[1]. In the event where more than one state reports a missing observation, we use the proportion of the state's employment in the upper region's value from each year for which both values are recorded[2]. After taking the average of the rate for all observable years, we apply the averaged rate to the years with the missing values. This approach assumes that the proportion of employment within the beverages and tobacco industry out of the upper-region's employment does not change significantly from year to year. For the year 1997 for which all the data are missing, employment data at the state level is generated using a concordance, or bridge, from the Standard Industrial Classification (SIC) to the NAICS following the approach of Peri (2012). The BEA is used to provide information on employment for each SIC industry up until 2001. In addition, the U.S. Census Bureau's report on the bridge between the NAICS and SIC[3] lists each NAICS code with the corresponding SIC coded industries that are grouped in it. For each SIC code, the establishments, sales, payroll and employees are also listed for each part of SIC that are mapped to the corresponding NAICS industry. The total values for each SIC industry are also listed. We need information on how much each SIC coded industry belongs to the NAICS food, beverages and tobacco industry (NAICS312). So, we first calculate the percentage of each SIC industry's number of employees that belong to the NAICS312 (from the first part of the report) out of the total number of employees within the SIC industry. We then map the SIC totals to NAICS312[4].

[1] For South Dakota (in the Plains) and Vermont (in New England)
[2] For Delaware we have 1999-2000 for reference, and for Mississippi we have 1998-2007 for reference.
[3] https://www2.census.gov/programs-surveys/cbp/technical-documentation/bridge-between-naics-and-sic/naics_sicbridge.pdf
[4] The SIC totals that are mapped to the NAICS312 are food and kindred products (SIC20), tobacco products (SIC21), 1.56% of food stores (SIC54) and 0.05% of wholesale trade (SIC50-51). For Delaware and Nevada, employment for tobacco products (SIC21) are missing so for these states we use the average of the nearest three years.

Appendix D: CES Production Function Estimation Results

Table D1: Production function estimates

	Estimation result		Marginal effect	
	(1) Nonlinear	(2) Linear	(3) Nonlinear	(4) Linear
$\boldsymbol{\beta}$	0.200**	0.201**		
	(0.089)	(0.094)		
$\boldsymbol{\gamma_1}$	-0.024	-0.017	-0.012	-0.009
	(0.028)	(0.030)	(0.014)	(0.015)
$\boldsymbol{\gamma_2}$	0.105**	0.104**	0.053**	0.052*
	(0.049)	(0.053)	(0.025)	(0.027)
$\boldsymbol{\gamma_3}$	0.128	0.130	0.064	0.065
	(0.092)	(0.105)	(0.046)	(0.052)
$\boldsymbol{\theta_1}$	-1.913	-0.114		
	(68.127)	(0.189)		
$\boldsymbol{\theta_2}$	-0.339	-0.009		
	(8.683)	(0.020)		
$\boldsymbol{\theta_3}$	0.149	-0.002		
	(8.189)	(0.037)		
Output elasticity of labor				
$\boldsymbol{1-\beta-\gamma_1-\gamma_2-\gamma_3}$	0.591***	0.582**		
	(0.126)	(0.141)		
Elasticity of substitution				
$\boldsymbol{\sigma_1}$	0.343	0.900***		
	(8.024)	(0.152)		
$\boldsymbol{\sigma_2}$	0.747	0.991***		
	(4.843)	(0.020)		
$\boldsymbol{\sigma_3}$	1.175	0.998***		
	(11.303)	(0.036)		
$\boldsymbol{\sigma_1 = 1}$	0.966	0.503		
$\boldsymbol{\sigma_2 = 1}$	0.877	0.660		
$\boldsymbol{\sigma_3 = 1}$	0.917	0.950		
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	240	240	240	240

Note: Standard errors are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Marginal effects ($\frac{dlnY}{dlnI} = \frac{dlnY}{dlnM}$) of locally grown and imported inputs are estimated as $\frac{\gamma}{2}$ based on the derivative we outline in Appendix A. Columns 1 and 3 are coefficients based on the nonlinear least squares (NLS) estimation. Standard errors are bootstrapped after 100 replications. Columns 2 and 4 are the estimates of the linear approximation estimated by ordinary least squares (OLS) with robust standard errors. For columns 1 and 2, we report the p-value for the test of elasticity of substitution between locally produced and imported input, $\boldsymbol{H_0: \sigma = 1}$.

Table D2: Production function estimates with extreme and mild drought

	Estimation result		Marginal effect	
	(1) Nonlinear	(2) Linear	(3) Nonlinear	(4) Linear
$\boldsymbol{\beta}$	0.199**	0.201**		
	(0.097)	(0.095)		
$\boldsymbol{\gamma_1}$	-0.025	-0.018	-0.012	-0.009
	(0.033)	(0.030)	(0.016)	(0.015)
$\boldsymbol{\gamma_2}$	0.106**	0.105*	0.053**	0.053*
	(0.048)	(0.054)	(0.024)	(0.027)
$\boldsymbol{\gamma_3}$	0.133*	0.136	0.067*	0.068
	(0.079)	(0.109)	(0.040)	(0.054)
$\boldsymbol{\theta_1}$	-2.131	-0.107		
	(66.451)	(0.167)		
$\boldsymbol{\theta_2}$	-0.342	-0.009		
	(0.982)	(0.021)		
$\boldsymbol{\theta_3}$	0.152	-0.004		
	(16.787)	(0.034)		
Output elasticity of labor				
$\mathbf{1-\beta-\gamma_1-\gamma_2-\gamma_3}$	0.586***	0.577***		
	(0.118)	(0.186)		
Elasticity of substitution				
$\boldsymbol{\sigma_1}$	0.3319	0.904***		
	(6.780)	(0.137)		
$\boldsymbol{\sigma_2}$	0.745	0.991***		
	(8.350)	(0.020)		
$\boldsymbol{\sigma_3}$	1.180	0.996***		
	(23.356)	(0.034)		
$\boldsymbol{\sigma_1 = 1}$	0.920	0.481		
$\boldsymbol{\sigma_2 = 1}$	0.976	0.645		
$\boldsymbol{\sigma_3 = 1}$	0.994	0.902		
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	240	240	240	240

Note: Standard errors are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Marginal effects ($\frac{dlnY}{dlnI} = \frac{dlnY}{dlnM}$) of locally grown and imported inputs are estimated as $\frac{\gamma}{2}$ based on the derivative we outline in Appendix A. Columns 1 and 3 are coefficients based on the nonlinear least squares (NLS) estimation. Standard errors are bootstrapped after 100 replications. Columns 2 and 4 are the estimates of the linear approximation estimated by ordinary least squares (OLS) with robust standard errors. For columns 1 and 2, we report the p-value for the test of elasticity of substitution between locally produced and imported input, $\boldsymbol{H_0: \sigma = 1}$.

Appendix E: Estimates for Maps

Table E1: Estimates and standard errors for Figure 7

Origin	Destination	SCTG01		SCTG02		SCTG03	
		Import channel	Std. err.	Import channel	Std. err.	Import channel	Std. err.
Alabama	Illinois	0.000	0.000	0.017	0.006	0.632	0.422
Arizona	Illinois	0.000	0.000	0.000	0.000	7.937	5.304
Arkansas	Illinois	0.001	0.003	4.321	1.614	3.129	2.091
California	Illinois	0.035	0.094	0.650	0.243	87.756	58.648
Colorado	Illinois	0.000	0.000	1.295	0.484	12.103	8.088
Connecticut	Illinois	0.000	0.000	0.000	0.000	0.334	0.223
Delaware	Illinois	0.000	0.000	0.012	0.004	0.610	0.408
Florida	Illinois	0.001	0.004	0.012	0.005	23.320	15.585
Georgia	Illinois	0.001	0.002	0.016	0.006	15.477	10.344
Idaho	Illinois	0.000	0.000	4.592	1.715	51.246	34.248
Illinois	Illinois	-114.470	305.999	1019.187	380.678	-673.574	450.154
Indiana	Illinois	3.939	10.530	583.688	218.014	450.463	301.048
Iowa	Illinois	1.463	3.912	349.342	130.483	675.796	451.640
Kansas	Illinois	0.027	0.072	75.989	28.383	3.055	2.042
Kentucky	Illinois	0.535	1.430	38.552	14.400	26.636	17.801
Louisiana	Illinois	0.000	0.000	11.764	4.394	6.499	4.343
Maine	Illinois	0.000	0.001	0.042	0.016	0.489	0.327
Maryland	Illinois	0.000	0.000	0.001	0.001	0.136	0.091
Massachusetts	Illinois	0.000	0.000	0.004	0.002	0.993	0.664
Michigan	Illinois	0.751	2.007	58.139	21.716	89.496	59.811
Minnesota	Illinois	0.256	0.685	94.398	35.259	112.138	74.943
Mississippi	Illinois	0.003	0.007	3.067	1.145	24.953	16.676
Missouri	Illinois	7.578	20.257	286.113	106.866	574.474	383.925
Montana	Illinois	0.000	0.000	0.000	0.000	0.003	0.002
Nebraska	Illinois	0.089	0.239	127.899	47.772	1.545	1.033
Nevada	Illinois	0.000	0.000	0.000	0.000	0.001	0.001
New Hampshire	Illinois	0.000	0.000	0.000	0.000	0.000	0.000
New Jersey	Illinois	0.002	0.006	0.051	0.019	1.964	1.313
New Mexico	Illinois	0.000	0.000	0.000	0.000	0.525	0.351
New York	Illinois	0.327	0.875	0.853	0.319	6.585	4.401
North Carolina	Illinois	0.003	0.007	0.021	0.008	11.769	7.865
North Dakota	Illinois	0.000	0.000	164.558	61.464	85.959	57.447
Ohio	Illinois	0.422	1.129	49.197	18.375	54.904	36.693
Oklahoma	Illinois	0.008	0.022	0.005	0.002	0.310	0.207
Oregon	Illinois	0.000	0.000	3.281	1.226	27.014	18.054
Pennsylvania	Illinois	0.042	0.113	0.119	0.044	2.477	1.655
Rhode Island	Illinois	0.006	0.015	0.000	0.000	0.000	0.000
South Carolina	Illinois	0.000	0.000	0.000	0.000	2.175	1.454
South Dakota	Illinois	0.071	0.191	200.561	74.912	42.574	28.453
Tennessee	Illinois	0.102	0.272	0.456	0.170	47.501	31.745
Texas	Illinois	0.000	0.000	12.292	4.591	83.256	55.641
Utah	Illinois	0.000	0.000	0.013	0.005	5.868	3.921
Vermont	Illinois	0.002	0.006	0.000	0.000	0.008	0.006
Virginia	Illinois	0.002	0.006	0.098	0.037	16.381	10.947
Washington	Illinois	0.000	0.000	0.000	0.000	16.897	11.292
West Virginia	Illinois	0.014	0.038	0.000	0.000	0.012	0.008
Wisconsin	Illinois	2.846	7.608	597.706	223.250	307.371	205.418
Wyoming	Illinois	0.000	0.000	0.000	0.000	1.947	1.301

Table E2: Estimates and standard errors for Figure 8

Origin	Destination	SCTG01		SCTG02		SCTG03	
		Export channel	Std. err.	Export channel	Std. err.	Export channel	Std. err.
Alabama	Illinois	0.000	0.001	-0.021	0.008	-0.115	0.077
Arizona	Illinois	0.001	0.001	0.000	0.000	-1.449	0.968
Arkansas	Illinois	0.007	0.018	-5.520	2.062	-0.571	0.382
California	Illinois	0.246	0.658	-0.830	0.310	-16.019	10.706
Colorado	Illinois	0.000	0.000	-1.654	0.618	-2.209	1.476
Connecticut	Illinois	0.000	0.000	0.000	0.000	-0.061	0.041
Delaware	Illinois	0.000	0.000	-0.015	0.006	-0.111	0.074
Florida	Illinois	0.010	0.028	-0.016	0.006	-4.257	2.845
Georgia	Illinois	0.006	0.017	-0.021	0.008	-2.825	1.888
Idaho	Illinois	0.000	0.000	-5.866	2.191	-9.354	6.252
Illinois	Illinois						
Indiana	Illinois	27.532	73.599	-745.625	278.499	-82.228	54.954
Iowa	Illinois	10.228	27.342	-446.263	166.684	-123.361	82.443
Kansas	Illinois	0.188	0.503	-97.072	36.257	-0.558	0.373
Kentucky	Illinois	3.738	9.993	-49.248	18.395	-4.862	3.249
Louisiana	Illinois	0.000	0.000	-15.028	5.613	-1.186	0.793
Maine	Illinois	0.003	0.007	-0.053	0.020	-0.089	0.060
Maryland	Illinois	0.000	0.000	-0.002	0.001	-0.025	0.017
Massachusetts	Illinois	0.000	0.001	-0.005	0.002	-0.181	0.121
Michigan	Illinois	5.248	14.028	-74.269	27.740	-16.337	10.918
Minnesota	Illinois	1.790	4.785	-120.587	45.041	-20.470	13.680
Mississippi	Illinois	0.019	0.050	-3.918	1.463	-4.555	3.044
Missouri	Illinois	52.964	141.582	-365.491	136.515	-104.865	70.082
Montana	Illinois	0.000	0.000	0.000	0.000	-0.001	0.000
Nebraska	Illinois	0.625	1.672	-163.383	61.025	-0.282	0.189
Nevada	Illinois	0.001	0.003	0.000	0.000	0.000	0.000
New Hampshire	Illinois	0.000	0.000	0.000	0.000	0.000	0.000
New Jersey	Illinois	0.015	0.040	-0.065	0.024	-0.359	0.240
New Mexico	Illinois	0.000	0.000	0.000	0.000	-0.096	0.064
New York	Illinois	2.288	6.115	-1.090	0.407	-1.202	0.803
North Carolina	Illinois	0.019	0.052	-0.026	0.010	-2.148	1.436
North Dakota	Illinois	0.000	0.000	-210.212	78.517	-15.691	10.486
Ohio	Illinois	2.952	7.892	-62.846	23.474	-10.022	6.698
Oklahoma	Illinois	0.058	0.155	-0.007	0.003	-0.057	0.038
Oregon	Illinois	0.000	0.000	-4.191	1.566	-4.931	3.296
Pennsylvania	Illinois	0.296	0.792	-0.152	0.057	-0.452	0.302
Rhode Island	Illinois	0.040	0.108	0.000	0.000	0.000	0.000
South Carolina	Illinois	0.000	0.000	0.000	0.000	-0.397	0.265
South Dakota	Illinois	0.499	1.333	-256.203	95.695	-7.772	5.194
Tennessee	Illinois	0.712	1.904	-0.582	0.217	-8.671	5.795
Texas	Illinois	0.000	0.000	-15.703	5.865	-15.198	10.157
Utah	Illinois	0.000	0.000	-0.016	0.006	-1.071	0.716
Vermont	Illinois	0.015	0.039	0.000	0.000	-0.002	0.001
Virginia	Illinois	0.015	0.039	-0.126	0.047	-2.990	1.998
Washington	Illinois	0.000	0.000	0.000	0.000	-3.084	2.061
West Virginia	Illinois	0.099	0.264	0.000	0.000	-0.002	0.001
Wisconsin	Illinois	19.892	53.176	-763.531	285.187	-56.108	37.497
Wyoming	Illinois	0.000	0.000	0.000	0.000	-0.355	0.238

Table E3: Estimates and standard errors for Figure 9

Origin	Destination	SCTG01		SCTG02		SCTG03	
		Export channel	Std. err.	Export channel	Std. err.	Export channel	Std. err.
Illinois	Alabama	0.023	0.062	-161.500	60.322	-8.387	5.605
Illinois	Arizona	0.000	0.000	0.000	0.000	-0.365	0.244
Illinois	Arkansas	0.072	0.193	-33.909	12.665	-5.746	3.840
Illinois	California	0.000	0.000	-152.868	57.098	-17.492	11.690
Illinois	Colorado	0.000	0.001	-0.011	0.004	-1.438	0.961
Illinois	Connecticut	0.000	0.000	-10.301	3.848	-0.291	0.194
Illinois	Delaware	0.000	0.000	0.000	0.000	-0.043	0.029
Illinois	Florida	0.000	0.000	-544.377	203.331	-19.389	12.958
Illinois	Georgia	0.040	0.107	-320.799	119.822	-15.795	10.556
Illinois	Idaho	0.000	0.000	0.000	0.000	-0.056	0.038
Illinois	Illinois						
Illinois	Indiana	12.463	33.317	-646.692	241.547	-63.881	42.692
Illinois	Iowa	8.274	22.117	-362.401	135.361	-27.754	18.548
Illinois	Kansas	0.030	0.080	-1.094	0.409	-3.196	2.136
Illinois	Kentucky	3.278	8.762	-130.134	48.606	-10.620	7.098
Illinois	Louisiana	0.000	0.000	-260.082	97.144	-34.507	23.061
Illinois	Maine	0.000	0.000	0.000	0.000	-0.009	0.006
Illinois	Maryland	0.000	0.000	-55.002	20.544	-2.559	1.710
Illinois	Massachusetts	0.000	0.000	-0.310	0.116	-0.732	0.489
Illinois	Michigan	7.535	20.143	-334.456	124.923	-19.203	12.834
Illinois	Minnesota	0.033	0.088	-20.731	7.743	-4.131	2.761
Illinois	Mississippi	0.076	0.204	-152.826	57.082	-9.888	6.608
Illinois	Missouri	8.625	23.056	-498.702	186.271	-66.968	44.755
Illinois	Montana	0.000	0.000	-0.002	0.001	-0.005	0.003
Illinois	Nebraska	0.012	0.032	-0.532	0.199	-0.641	0.428
Illinois	Nevada	0.001	0.002	0.000	0.000	-0.101	0.067
Illinois	New Hampshire	0.000	0.000	0.000	0.000	-0.065	0.044
Illinois	New Jersey	0.002	0.006	-0.780	0.291	-1.957	1.308
Illinois	New Mexico	0.000	0.000	-0.075	0.028	-0.111	0.074
Illinois	New York	0.000	0.000	-219.372	81.938	-8.854	5.917
Illinois	North Carolina	0.046	0.123	-40.698	15.201	-1.354	0.905
Illinois	North Dakota	0.000	0.000	0.000	0.000	-0.022	0.014
Illinois	Ohio	1.850	4.946	-101.235	37.812	-12.177	8.138
Illinois	Oklahoma	0.020	0.055	0.000	0.000	-0.099	0.066
Illinois	Oregon	0.004	0.010	-0.008	0.003	-0.454	0.304
Illinois	Pennsylvania	1.722	4.604	-69.873	26.098	-13.700	9.156
Illinois	Rhode Island	0.000	0.000	0.000	0.000	-0.041	0.027
Illinois	South Carolina	0.000	0.000	-22.385	8.361	-0.497	0.332
Illinois	South Dakota	0.007	0.019	-0.114	0.043	-0.015	0.010
Illinois	Tennessee	2.697	7.211	-414.302	154.746	-18.728	12.516
Illinois	Texas	0.002	0.006	-130.416	48.712	-9.804	6.552
Illinois	Utah	0.000	0.000	0.000	0.000	-0.611	0.408
Illinois	Vermont	0.000	0.000	0.000	0.000	-0.656	0.438
Illinois	Virginia	0.000	0.000	-3.044	1.137	-0.454	0.304
Illinois	Washington	0.000	0.000	-0.078	0.029	-0.051	0.034
Illinois	West Virginia	0.000	0.000	0.000	0.000	-0.239	0.159
Illinois	Wisconsin	15.038	40.199	-408.045	152.409	-65.663	43.883
Illinois	Wyoming	0.023	0.062	-161.500	60.322	-8.387	5.605

Table E4: Estimates and standard errors for Figure 10

State	SCTG01		SCTG02		SCTG03	
	Inward effect (row sum)	Std. err.	Inward effect (row sum)	Std. err.	Inward effect (row sum)	Std. err.
Alabama	31.527	84.278	-830.040	310.029	-128.1902	85.670
Arizona	29.130	77.869	-766.918	286.453	-118.4419	79.156
Arkansas	41.393	110.652	-1089.797	407.051	-168.3068	112.481
California	284.044	759.301	-7478.246	2793.207	-1154.9307	771.849
Colorado	35.037	93.660	-922.443	344.543	-142.4609	95.208
Connecticut	17.887	47.816	-470.935	175.899	-72.7305	48.606
Delaware	6.439	17.212	-169.518	63.317	-26.1801	17.496
Florida	91.411	244.360	-2406.664	898.916	-371.6821	248.398
Georgia	73.826	197.351	-1943.684	725.987	-300.1800	200.612
Idaho	19.267	51.504	-507.253	189.465	-78.3395	52.355
Illinois	129.507	346.196	-3409.637	1273.537	-526.5800	351.917
Indiana	56.614	151.339	-1490.520	556.726	-230.1940	153.840
Iowa	82.242	219.847	-2165.240	808.741	-334.3969	223.480
Kansas	44.299	118.419	-1166.295	435.624	-180.1211	120.376
Kentucky	35.525	94.965	-935.300	349.345	-144.4465	96.535
Louisiana	24.939	66.668	-656.602	245.248	-101.4047	67.770
Maine	7.968	21.301	-209.788	78.358	-32.3994	21.653
Maryland	36.227	96.842	-953.785	356.249	-147.3014	98.443
Massachusetts	37.188	99.411	-979.081	365.697	-151.2080	101.053
Michigan	59.866	160.033	-1576.139	588.705	-243.4169	162.677
Minnesota	66.899	178.832	-1761.295	657.863	-272.0121	181.788
Mississippi	19.287	51.558	-507.789	189.665	-78.4223	52.410
Missouri	59.490	159.028	-1566.244	585.010	-241.8888	161.656
Montana	4.090	10.934	-107.686	40.222	-16.6309	11.115
Nebraska	54.766	146.400	-1441.876	538.557	-222.6815	148.820
Nevada	11.821	31.601	-311.230	116.248	-48.0660	32.123
New Hampshire	6.261	16.738	-164.848	61.573	-25.4590	17.014
New Jersey	76.668	204.947	-2018.495	753.930	-311.7338	208.334
New Mexico	10.400	27.800	-273.798	102.267	-42.2851	28.259
New York	117.654	314.511	-3097.573	1156.978	-478.3851	319.708
North Carolina	95.758	255.978	-2521.092	941.656	-389.3542	260.208
North Dakota	7.886	21.082	-207.633	77.553	-32.0666	21.430
Ohio	101.172	270.450	-2663.625	994.893	-411.3667	274.919
Oklahoma	26.091	69.746	-686.922	256.573	-106.0873	70.899
Oregon	28.471	76.108	-749.573	279.974	-115.7631	77.365
Pennsylvania	107.832	288.255	-2838.982	1060.391	-438.4487	293.018
Rhode Island	3.776	10.093	-99.404	37.129	-15.3518	10.260
South Carolina	23.022	61.542	-606.119	226.392	-93.6082	62.559
South Dakota	10.493	28.050	-276.258	103.185	-42.6649	28.513
Tennessee	57.954	154.922	-1525.800	569.903	-235.6426	157.482
Texas	163.610	437.359	-4307.488	1608.894	-665.2428	444.587
Utah	18.846	50.379	-496.171	185.326	-76.6281	51.211
Vermont	9.394	25.113	-247.334	92.382	-38.1979	25.528
Virginia	70.137	187.490	-1846.561	689.711	-285.1806	190.588
Washington	47.184	126.131	-1242.245	463.992	-191.8508	128.215
West Virginia	4.727	12.636	-124.451	46.484	-19.2200	12.845
Wisconsin	92.984	248.565	-2448.075	914.383	-378.0776	252.672
Wyoming	1.390	3.716	-36.598	13.670	-5.6521	3.777

Table E5: Estimates and standard errors for Figure 11

State	SCTG01		SCTG02		SCTG03	
	Outward effect (column sum)	Std. err.	Outward effect (column sum)	Std. err.	Outward effect (column sum)	Std. err.
Alabama	31.402	83.943	-149.729	55.925	-100.049	66.864
Arizona	122.363	327.099	-19.202	7.172	-224.094	149.764
Arkansas	19.589	52.364	-148.791	55.575	-80.293	53.660
California	29.837	79.761	-374.555	139.900	-545.975	364.879
Colorado	9.485	25.354	-584.021	218.138	-114.676	76.639
Connecticut	21.623	57.802	-158.655	59.259	-97.036	64.850
Delaware	31.903	85.282	-817.682	305.413	-63.241	42.265
Florida	31.423	84.000	-99.475	37.155	-346.205	231.371
Georgia	48.467	129.560	-341.520	127.561	-230.088	153.769
Idaho	26.902	71.914	-914.393	341.536	-326.225	218.018
Illinois	61.851	165.339	-5097.156	1903.844	-448.758	299.908
Indiana	108.222	289.297	-5957.264	2225.104	-333.352	222.781
Iowa	74.744	199.805	-4051.801	1513.392	-451.881	301.995
Kansas	85.025	227.288	-5006.458	1869.967	-148.323	99.125
Kentucky	66.041	176.541	-631.962	236.045	-145.233	97.060
Louisiana	42.665	114.052	-312.322	116.656	-172.207	115.087
Maine	10.368	27.715	-36.189	13.517	-31.748	21.218
Maryland	58.079	155.257	-946.934	353.690	-165.181	110.391
Massachusetts	23.587	63.052	-137.532	51.370	-74.929	50.076
Michigan	31.587	84.439	-2195.350	819.987	-402.337	268.885
Minnesota	114.206	305.293	-3741.872	1397.630	-373.140	249.372
Mississippi	92.356	246.885	-207.433	77.478	-111.931	74.804
Missouri	105.413	281.788	-2861.994	1068.986	-299.934	200.448
Montana	23.941	63.998	-919.034	343.269	-64.525	43.123
Nebraska	43.501	116.287	-7132.734	2664.155	-340.818	227.771
Nevada	105.741	282.665	-2.038	0.761	-103.417	69.114
New Hampshire	11.396	30.462	-21.228	7.929	-15.999	10.692
New Jersey	25.229	67.441	-596.645	222.854	-368.880	246.525
New Mexico	29.584	79.083	-99.656	37.223	-16.686	11.151
New York	62.818	167.924	-1085.400	405.409	-352.418	235.523
North Carolina	97.041	259.409	-439.857	164.292	-198.434	132.615
North Dakota	5.009	13.391	-3616.203	1350.692	-329.170	219.987
Ohio	81.854	218.811	-5005.963	1869.782	-352.465	235.555
Oklahoma	95.740	255.932	-995.590	371.864	-203.255	135.837
Oregon	70.307	187.945	-306.140	114.347	-345.219	230.712
Pennsylvania	140.215	374.821	-1106.175	413.169	-227.210	151.846
Rhode Island	11.416	30.518	-5.460	2.039	-24.288	16.232
South Carolina	102.710	274.563	-208.490	77.873	-136.253	91.059
South Dakota	39.537	105.689	-2168.033	809.784	-271.194	181.241
Tennessee	49.189	131.492	-878.597	328.166	-300.442	200.788
Texas	8.830	23.605	-1126.274	420.676	-332.674	222.328
Utah	30.648	81.928	-37.146	13.874	-21.879	14.622
Vermont	2.797	7.478	-138.829	51.854	-8.234	5.503
Virginia	43.907	117.371	-711.531	265.765	-145.836	97.463
Washington	17.648	47.177	-414.931	154.981	-259.887	173.685
West Virginia	38.717	103.498	-81.017	30.261	-20.805	13.904
Wisconsin	32.200	86.076	-2324.254	868.135	-165.173	110.386
Wyoming	25.288	67.598	-89.535	33.442	-38.884	25.986