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, the agrifood supply chain faces challenges from a growing population and less predictable weather conditions. Extreme weather events decrease agricultural yield, which leads to changes in the domestic trade of agricultural products and, in turn, in the manufacturing of food products. This paper investigates the extent to which food manufacturing in any single state is dependent on drought events affecting locally sourced inputs and/or imported inputs. For this purpose, we estimate the food manufacturing production function in a two-stage process. In the first stage, we assess the role of drought on trade in animals and fish (SCTG 01), cereal grains (SCTG 02), and all other crop products (SCTG 03). In the second stage, we estimate a nested production function for processed food at the state level. Our findings indicate that the agrifood supply chain always adapt to a weather-induced shock on inputs but, depending on the location of the latter, it leads to either an increase or a decrease in a state's food manufacturing production. We end with simulations showing how drought events affect food manufacturing production in California and Texas, the largest players in the national agrifood network.

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1 Introduction

The U.S. agrifood supply chain faces pressure from a growing population and less predictable weather conditions (Battisti and Naylor, 2009). Climate change has already led some areas of the country to experience more frequent and intense extreme weather events and the trend will intensify in the decades to come (IPCC, 2022). Extreme weather events such as droughts and extreme moisture reduce agricultural outcomes (Lesk et al., 2016; Kuwayama et al., 2019; Vogel et al., 2019; Cheng et al., 2022), perturbate the domestic trade of agricultural products (Dall'erba et al., 2021; Nava et al., 2023) and, in turn, the manufacturing of food products since the former are necessary inputs in the production of the latter (Davis et al., 2021). 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 (Dall'erba et al., 2021). For states that do not specialize in agriculture but hope to maintain their purchases of crops and livestock for food manufacturing, such as New Jersey and Pennsylvania, this type of event might lead to more expensive inputs. For instance, the prices of wheat, corn, and soybeans increased by 20.2%, 20.5%, and 13% respectively after a drought affected a large portion of the Midwest in 2012 (U.S. BLS, 2012).

Central to society's capacity to address climate adaptation is the ability of trade to guarantee the resiliency of supply chains from producers to the agrifood industry and then to final consumers. Trade adjustments reduce welfare losses in the agricultural sector (Gouel and Laborde, 2021), partially compensate for losses in yields (Huang et al., 2011) and profits (Dall'erba et al., 2021), and mitigate price volatility (Rutten et al., 2013; Baldos and Hertel, 2015). Yet, there is a paucity of studies focusing on the impact of disruption in the downstream food supply chain. Exceptions include Laber et al. (2023) and Malik et al. (2022) who focus on the impact of the Ukraine-Russia war on the global food system and on extreme weather events on the Australian food system respectively. A notable difference with our work is that we do not treat the agrifood trade as fixed. Indeed, the cascading impact of supply disruption is contingent on the restructuring of import relations after a perturbation has occurred, as advocated in the trade literature.

Yet, a major departure with the current trade literature is that the traditional focus on agrifood flows has mostly been at the international level due to the paucity of interregional trade data at the domestic level (Rutten et al., 2013; Gouel and Laborde, 2021; Laber et al., 2023). Nevertheless, the United States is a notable exception (Dall'erba et al., 2021; Nava et al., 2023) because data are available from the Bureau of Transportation Statistics (BTS) and a majority of the country's agrifood products are for the domestic market, even if there are notable differences in the degree of international exposure by commodity. Over the past decade, the share of U.S. agrifood products (both nonmanufactured and manufactured) sold internationally has remained steady at 20% (based on USDA ERS, 2024). Similarly, the share of imports for food and beverages consumption from the international market has remained low at approximately 15% (based on USDA ERS, 2024). In addition, the BTS data used in this manuscript distinguishes the interstate trade flows which have a U.S. destination for the final or intermediate demand versus interstate trade for U.S. destinations such as New Orleans, Louisiana, which are used as a port of departure for international exports. Our manuscript focuses only on trade flows for the domestic market.

The domestic focus that this manuscript adopts means that the capacity of adaptation or propagation of risks due to trade dependency 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 as those of the international level: yield losses are substituted with imports or are transmitted through decreased exports, hence having implications beyond the location where the perturbation took place (Marchand et al., 2016; Inoue and Todo, 2019; Bertassello et al., 2023). As a result, trade has a short-run potential to mitigate or accentuate the disruptive effects of extreme weather. 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 and beverages in the United States.

In order to understand the vulnerability and resilience of the U.S. agrifood supply chain to extreme weather events, we estimate a Cobb-Douglas (CD) production function of food manufacturing as a function of labor, capital, and agricultural inputs, with the novelty that each individual input follows a constant elasticity of substitution (CES) across the various locations it comes from. The latter element is grounded in the theory of the gravity model of bilateral trade where inputs sourced from different trading partners have Armington-CES (Anderson and van Wincoop, 2003; Anderson and Yotov, 2016). It allows us to assess whether locally produced inputs substitute or complement imported inputs in food production. This construct leads us to investigate how a weather shock propagates through interregional and intersectoral relationships embedded in the production process of the downstream sector. To the best of our knowledge, this endeavor has never been done before. Ultimately, this approach allows us to visualize the agrifood supply chain, detect the key hubs and spokes in the system and identify the risks of propagation of a shock on yield. It is important because, from this work, we can suggest stakeholders where to focus their mitigation efforts.

The rest of this paper is organized as follows. Section 2 describes how we combine the structural equations of a gravity model of trade (stage 1) with the ones of a nested production function (stage 2) in order to include both interregional and intersectoral linkages in the analysis of the impact of extreme weather on food manufacturing. Section 3 presents the data and shows their distribution across states. Section 4 starts by presenting and discussing the econometric estimates and then moves on to simulating the impact of a local and distant weather shock on food manufacturing in California and Texas, the two largest players in the nation's food supply chain. Finally, section 5 summarizes the results and provides some concluding remarks.

2 Empirical model

In this section, we formulate our production function with inputs that are sourced locally or from another sector and another location.

The final output of manufactured agrifood 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 primary agricultural inputs I^A (superscript A denotes agricultural production) needed in the food manufacturing sector. Following the seminal structural gravity framework with CES input demand (Anderson and van Wincoop, 2003; Anderson and Yotov, 2016), 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.[1] This is expressed as:

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

[1] Such nested production functions with input as a sub-aggregate appear in previous literature. Specifically, for input sub-aggregates of energy for the electricity sector (Papageorgiou et al., 2017) and materials for multinational firms with manufactured outputs (Boehm et al., 2019).

where PT_j^F is the technological productivity of the manufactured food sector, $\alpha, \beta,$ and γ are factor shares, and I^A is noted as (2). By setting the aggregate CD production function, we implicitly 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.

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

We are interested in estimating, σ, the elasticity of substitution between locally sourced and imported agricultural inputs. The elasticity of substitution is nonnegative as defined by production theory. Traded agricultural inputs are assumed common across states. The parameter δ is the share of I_j^A within the aggregate measurement of agricultural inputs. 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

Agricultural inputs that enter the manufactured food production process (1) require from us to distinguish local from imported inputs. We do this by relying on a state-to-state structural gravity model of trade as derived in Anderson and 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 in equation (5a) and the importing state's size Y_j^F is defined as in equation (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 an extreme weather event S^A affects the exporting state i and/or the importing state j. There is no equivalent S^F term needed since food manufacturing activities take place indoors and thus are not subject to a direct detrimental effect of weather. As a result, the trade of primary agricultural inputs is dependent on weather shocks at both origin and destination, on the capacity of exporters and importers to produce agricultural commodities (Z_i^A and 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 well documented in Dall'erba et al. (2021): for the exporters of agricultural goods, production losses following a weather shock S_i^A would mean less available output to be exported and/or relying on stocks for exports. For importers, production losses following a shock S_j^A are substituted with imports, hence creating trade. This means that the elasticity of substitution σ_θ between locally produced and imported agricultural inputs is determined depending on where the event of extreme weather disruption takes place: at the point of origin, of destination or in both locations.

The second components of Equation (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, geographic, 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 (hereafter MRTs) measure the state's ease or impediment to market access as defined as:

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

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

In equations (6a) and (6b), Π_i is the outward multilateral resistance for the exporting state, and P_j is the inward multilateral resistance for the importing state. Each trading partner is weighted 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.

Equation (7) is an estimable specification of equation (4) in a panel setting measured over years t and across agricultural commodities k:

$$I_{ijkt}^{AF} = \exp\{a + \ln X_{ikt}^A + \ln Y_{jkt}^F - (1-\sigma_\rho)\ln\Pi_{ikt} - (1-\sigma_\rho)\ln \mathrm{P}_{jkt} + \mu_{ij}\} + \epsilon_{ijkt}, \tag{7}$$

where $a = -\ln X_{kt}$, $\mu_{ij} = (1-\sigma_\rho)\ln t_{ij}$, and ϵ_{ijkt} is the stochastic term. Equation (7) includes pairwise fixed effects μ_{ij} which account for all time-invariant factors that vary at the exporter-importer level. It provides a systematic account of the effects of all time-variant bilateral trade costs that appear in a domestic setting such as distance, shared-border, home-effect, connection by boat or other factors that may have shaped the current interstate highway and railway systems.

In Equation (7), the exporter- and importer-size terms are parametrized as:

$$X_{ikt} = \exp\{\alpha_k^O \ln D_{ikt}^A + \delta_k^O \ln W_{ikt}^A + \lambda_{1k}^O \ln G_{ikt}^A + \lambda_{2k}^O \ln T_{ikt}^A + \lambda_{3k}^O \ln R_{ikt}^A + \mu_{CZit}\}, \tag{8a}$$

$$Y_{jkt} = \exp\{\alpha_k^D \ln D_{jkt}^A + \delta_k^D \ln W_{jkt}^A + \lambda_{1k}^D \ln G_{jkt-1}^F + \lambda_{2k}^D \ln T_{jkt}^A + \lambda_{3k}^D \ln R_{jkt}^A + \ln P_{jt}^A + \mu_{CZjt}\}, \tag{8b}$$

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[2] production (Lesk et al., 2016; Escarcha et al., 2018; Ray et al., 2018); 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 (GDD) of the growing season, and R_{ikt}^A is the precipitation during the

[2] SCTG 01 also includes fish. However, livestock account for the largest share of output and intermediate input demand for the manufactured food and beverage sector according to the Input-Output table.

growing season. The same corresponding variables are included for the importer j's size terms. Note that the importers' G^F_{jkt-1} is the value-added 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 value-added of food and beverages is the intermediate demand for agricultural commodities, it only partially represents the state-level demand. Hence, population P^A_{jt} is included to capture household demand. μ_{CZit} and μ_{CZjt} are terms that capture time-variant factors that vary at the climate-zone level, such as agricultural price changes.

While the multilateral resistance terms (MRTs) of equations (6) and (7), Π_{ikt} and P_{jkt}, are regularly the choice to fully control for both with exporter-time and importer-time fixed effects (Anderson and van Wincoop, 2003; Yotov et al., 2016), they will not be used here as they would subsume all factors that vary along the exporter-time and importer-time dimensions, including the extreme weather shocks. Therefore, we approximate the MRTs by equation (9) that follows the approach of Baier and Bergstrand (2009) that provides virtually identical coefficients without measurement errors:

$$-\left(1-\sigma_\rho\right)\ln\Pi_{ikt} - \left(1-\sigma_\rho\right)\ln P_{jkt} = \phi_{1k}\mathrm{MRT}_{ijkt}\left(\ln Dist_{ij}\right) + \phi_{2k}\mathrm{MRT}_{ijkt}\left(C_{ij}\right) + \phi_{3k}\mathrm{MRT}_{ijkt}\left(H_{ij}\right). \qquad (9)$$

Taking the log of distance as an example, $\mathrm{MRT}_{ijkt}\left(\ln Dist_{ij}\right)$ is approximated as $\sum_{i=1}^{N} m_{ikt}\ln Dist_{ij} + \sum_{j=1}^{N} m_{jkt}\ln Dist_{ij} - \sum_{i=1}^{N}\sum_{j=1}^{N} m_{ikt}m_{jkt}\ln Dist_{ij}$ where $m_{ikt} = X_{ikt}/X_{kt}$ is the exporter's production relative to total U.S. production, and $m_{jkt} = Y_{ikt}/Y_{kt}$ is the importer's expenditure relative to total U.S. expenditure. The same MRTs are approximated for the contiguity (C_{ij}) and home-state (H_{ij}) dummy variables.

We will estimate the gravity model of trade applying the Poisson Pseudo-Maximum Likelihood (PPML)[3] estimator (Santos Silva and Tenreyro, 2006, 2011) separately for each agricultural commodity: animals and fish ($k = 1$), cereal grains ($k = 2$), and other agricultural goods ($k = 3$). In addition, since our analysis focuses on the role of locally produced agricultural

[3] The PPML estimator outperforms the OLS estimator to estimate the gravity model for several reasons. First, estimating the OLS estimator will drop the zero trade flows. We are dealing with disaggregated trade by sector, and the proportion of zero trade flows for animals and fish (01), cereal grains (02), and other agricultural products (03) is 25%, 20% and 25% respectively. Second, the presence of heteroskedasticity inherent in trade data would lead to biased and inconsistent OLS estimates (see Santos Silva and Tenreyro (2006) for details).

inputs on the production of food manufacturing, we include terms related to within-state weather as:

$$I_{ijkt}^{A} = \exp\{a + \alpha_k^H I(i=j) \times \ln D_{i=jkt}^{A} + \alpha_k^O I(i \neq j) \times \ln D_{ikt}^{A} + \alpha_k^D I(i \neq j) \times \ln D_{jkt}^{A} \quad (10)$$
$$+ \delta_k^H I(i=j) \times \ln W_{i=jkt}^{A} + \delta_k^O I(i \neq j) \times \ln W_{ikt}^{A} + \delta_k^D I(i \neq j) \times \ln W_{ikt}^{A}$$
$$+ \boldsymbol{W}_{i=jkt}' \boldsymbol{\lambda}_k^H + \boldsymbol{X}_{ikt}' \boldsymbol{\lambda}_k^O + \boldsymbol{Y}_{jkt}' \boldsymbol{\lambda}_k^D + \boldsymbol{MRT}_{ijkt}' \boldsymbol{\phi}_k$$
$$+ \mu_{ij} + \mu_{CZit} + \mu_{CZjt}\} + \epsilon_{ijkt},$$

where I_{ijkt} is the volume of traded agricultural goods. The first term, with the parameter α_k^H, captures how locally-traded commodities (or commodities produced that are consumed within a state) react to a drought on available local agricultural products (as represented by the interaction with indicator variable $I(i=j)$). The drought-effect on exports (α_k^O) and imports (α_k^D) are drought terms interacted with indicator variable $I(i \neq j)$ that measure the effect of drought on all intrastate trade. Similarly, we have parameter δ_k^H to measure the within-state effect of wetness while parameters δ_k^O (for exports) and δ_k^D(for imports) focus on the impact on interstate trade. The within-state weather effects (e.g., GDD and precipitation) are captured by the vector $\boldsymbol{\lambda}_k^H$. The weather (e.g., GDD and precipitation) and economic effects (e.g., agricultural and manufactured food production) on exports and imports are similarly captured by $\boldsymbol{\lambda}_k^O$ and $\boldsymbol{\lambda}_k^D$, respectively. The MRTs effects are captured by the vector $\boldsymbol{\phi}_k$, where $\boldsymbol{MRT}_{ijkt}'$ is composed of approximated MRTs. Finally, the error term ϵ_{ijkt} is clustered by state-pair.

The second specification involves defining drought with two bins, noted s, one capturing extreme conditions ($s = 1$ when SPEIs above or equal to the threshold of 1.3) and the other one capturing mild conditions ($s = 2$ when SPEI is below 1.3 in absolute value) as in equation (11):

$$I_{ijkt}^{A} = \exp\{\sum_{s=1}^{2} \alpha_{ks}^H I(i=j) \times \ln D_{ikts}^{A} + \sum_{s=1}^{2} \alpha_{ks}^O I(i \neq j) \times \ln D_{ikts}^{A} + \sum_{s=1}^{2} \alpha_{ks}^D I(i \neq j) \times \ln D_{jkts}^{A} \quad (11)$$
$$+ \delta_k^H I(i=j) \times lnW_{ikt}^{A} + \delta_k^O I(i \neq j) \times lnW_{ikt}^{A} + \delta_k^D I(i \neq j) \times lnW_{ikt}^{A}$$
$$+ \boldsymbol{W}_{ijkt}' \boldsymbol{\lambda}_k^H + \boldsymbol{X}_{ikt}' \boldsymbol{\lambda}_k^O + \boldsymbol{Y}_{jkt}' \boldsymbol{\lambda}_k^D + \boldsymbol{MRT}_{ijkt}' \boldsymbol{\phi}_k$$
$$+ \mu_{ij} + \mu_{CZit} + \mu_{CZjt}\} + \epsilon_{ijkt}.$$

2.2. Production function of manufactured food

The empirical specification for the second stage can be expressed as a nested production function for manufactured food that includes labor, capital, and the k subaggregates of agricultural inputs as follows:

$$Y_{jt} = PT_j L_{jt}^{(1-\beta-\sum_k \gamma_k)} K_{jt}{}^{\beta} \prod_{k=1}^{3} I_{jkt}^{\gamma_k}. \quad (12)$$

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

$$I_{jkt} = \left[\left(\hat{I}_{j=ikt}{}^{\frac{\sigma_k-1}{\sigma_k}} + \left(\sum_{j\neq i}^{48} \hat{I}_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right)\right]^{\frac{\sigma_k}{\sigma_k-1}}. \quad (13)$$

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

$$lnY_{jt} = a_j + a_t + \left(1 - \beta - \sum_{k=1}^{3} \gamma_k\right) \ln L_{jt} + \beta \ln K_{jt} \quad (14)$$

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

In equation (14), Y_{jt} is total production of the food and beverage manufacturing sector; L_{jt} measures the aggregate labor; K_{jt} is the aggregate capital; $\hat{I}_{j=i,k,t}$ is the predicted local input from equation (10) with $k = 1$ for animals and fish, $k = 2$ for cereal grains, and $k = 3$ for the remaining agricultural goods. The parameters β, γ_1, γ_2, and γ_3 are the output elasticities of capital and each agricultural commodity, respectively. The elasticity of substitution between locally sourced and imported commodity k is captured by σ_k as both enter the food manufacturing production function. a_j and a_t are two-way fixed effects, and ε_{jt} is the error term clustered at the state level.

In the specification, we assume constant returns to scale where the output elasticities of aggregated capital, aggregated labor and sub-aggregate of agricultural commodities sum up to 1 while substitution between local and imported agricultural inputs by commodity-type is warranted. Our setting is based on two reasons. First, the k = 1, 2, 3 input commodity groups are hardly substitutable; second, a nested CES production function where all input categories would be substitutable would not allow us to attain parsimony of estimation (Fuss et al., 1978). There would be more parameters to estimate such as the degree of substitution between local live animals and imported grains, which we believe is not pertinent.

We first run the non-linear least squares (NLS) estimation of equation (14) without imposing restrictions on the elasticity of substitution.[4] Next, we estimate equation (14) with the ordinary least squares (OLS) regression where we impose two restrictions. First, we set the elasticity of substitution for each primary agricultural input group to be equal to one (or a CD relationship). Second, we constrain the output elasticities across locally sourced and imported inputs to be the same within each agricultural commodity group. This hypothesis reflects that the same crop product, no matter where it is produced, will have a homogeneous effect on agrifood production. To test this assumption, we conduct a Wald test for each primary input group where the null hypothesis is that the coefficients of locally sourced and imported inputs are equal and find out that the hypothesis could not be rejected at 1% level.

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 MRTs as well as the weather conditions and production in the places of origin i.

3 Data

3.1 Gravity model of agricultural trade

The data on the state-to-state trade of animals and fish (SCTG 01)[5], cereal grains (SCTG 02), and

[4] For the NLS estimation, we used the “nl” command in Stata with predetermined initial values without using grid search.
[5] The FAF uses the Standard Classification of Transported Goods (SCTG) coding scheme to group products into 43 commodities.

other agricultural products (SCTG 03) come from the Freight Analysis Framework (FAF, 2023).[6] We compile a dataset based on the quinquennial U.S. domestic trade flows of the FAF for the five years between 1997–2017. We begin by excluding flows that enter or leave the United States so that we include only freight movements and agrifood production for the domestic market and for all modes of transportation (e.g., truck, rail, water, and multiple modes). The data we compile covers 34,560 data points (48 states × 48 states × 5 years × 3 commodities). We also include intrastate flows for two reasons: first, it is consistent with our framework where destination states choose between local and imported agricultural inputs. Second, including intrastate flows reduces 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 (Yotov, 2022). All the measures are adjusted to 2012 U.S. dollars using the corresponding producer price index (FAF, 2023).

The exporting state's capacity to produce agricultural commodities is measured as the sum of the flow amounts in U.S. dollars that are exported to all the states (including interstate and within-state). The trade flows of agricultural commodities come from the FAF. In the gravity model, demand emanating from the importing states is captured by the one-year lagged production of the processed food sector. The lagged value allows us to mitigate endogeneity with the stage two dependent variable. Production is measured as the value added of food and beverages (including tobacco), as classified according to the North American Industry Classification System (NAICS) with code NAICS 312 from the Bureau of Economic Analysis (BEA, 2023b). The value added is weighted to account for the relative share of food and beverages that demand each of the three agricultural inputs, a share reported in Table 1 for each input (computed using the national Input-Output table from IMPLAN, 2020). About 76.7% of SCTG 01, 57.9% of SCTG 02 and 33.7% of SCTG 03 are used as inputs in the production of

[6] We chose FAF over another widely used interstate trade data set, the Commodity Flow Survey (CFS), for several reasons. First, the CFS is collected by surveying shipping firms in industries of mining, manufacturing, wholesale trade, auxiliaries, and select retail and service trade. Some out-of-scope industries such as agriculture, resource extraction, construction, and service sectors are not surveyed because their concept of shipment does not align with the CFS classification or sampling method. Therefore, it does not represent the actual universe of U.S. trade flows especially for agriculture. The BTS puts together the CFS responses and the missing information from USDA's National Agricultural Statistics Service (USDA NASS). The FAF, therefore, better represents shipments of crops and livestock. Another advantage of the FAF is that data over the years from 1997 to 2017 are comparable. In CFS there is extensive censoring for pre-2012 data due to differences from coverage of industries using different classification systems: the North American Industry Classification System (NAICS) and Standard Industrial Classification (SIC).

SCTG 04–09. We used data from the BEA as it provides value added for the manufacturing food industry for every five years from 1996 to 2011,[7] years which are not available in the FAF. The real values are deflated to 2012 U.S. dollars using the implicit price deflator (from the BEA, 2023a). We acknowledge that a one-year lagged production of manufactured food could be autocorrelated with production at t.[8] However, the final production of manufactured food in the second stage is the total produced value of SCTG 04–09 goods while the demand in stage 1 is specifically for the manufactured food that demands staple crops and livestock. Table 1 also shows that about 5.6–26.2% of SCTG 01–03 commodities are sold to households for final consumption which we capture through population size data (from the U.S. Census Bureau, 2023).

Drought (wetness) is measured as the absolute values of the negative (positive) measures of the Standardized Precipitation Evapotranspiration Index (SPEI)[9] with weather data obtained from the ERA5-Land database (Muñoz Sabater, 2019). We create SPEIs at the monthly and county-level, and growing degree days (GDD) and precipitation at the daily and county-level. We then aggregate monthly SPEI observations for 01–03 commodities to growing season-weighted measurements at the annual level.[10] Next, we aggregate county-level measurements to the state-level for each of the 01–03 commodities using spatial weights based on farmland acres per county.[11] 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 weather controls, we aggregate daily, county-level GDD and precipitation

[7] Production at the state level for all the industries classified by the NAICS 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. Details are in Appendix A.

[8] Approaches such as the Arellano-Bond GMM for resolving endogeneity by using the lagged dependent variables is not applicable in our analysis because the dimension of stage 1 is state-pair by year while that of stage 2 is state by year.

[9] The ERA5-Land database provides daily weather data at a spatial resolution of 4km over farmland areas from 1981 to 2019. SPEI is a standardized index which, for each locality, reports the deviation of current drought or wetness conditions from the locality's historical distribution. Negative/positive values indicate dry/moist conditions in the root-zone soil.

[10] Growing season is defined as the middle date of the planting period (the start date of the growing season) and the harvesting period (as the end date) of all the products within the SCTG 02 and SCTG 03 categories. The usual planting and harvesting dates are from the USDA (2022). For SCTG 01, we used year-long SPEI values since there is no growing season for animals and fish.

[11] The weights are based on the farmland area of each product classified in SCTG 02/03 from the USDA Farmland Service Agency (USDA FSA, 2022). For SCTG 01, we used information on county-level total sales of each livestock product from the USDA NAAS Census of Agriculture (USDA NASS, 2023).

to the annual, state level using the same spatial and temporal weights for each agricultural commodity as for drought and wetness.

Because we approximate the MRTs for three bilateral variables – distance, contiguity and within-state dummy variable – for our gravity model of agricultural trade, we collect distances between states as measured by 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, we use the average shipment distance as reported by the CFS and we average it over all periods. This approach allows us to avoid the typical issues associated with the geometric computation of within-state distance highlighted by Mayer and Head (2002). This approach is in line with previous domestic trade literature (Szewerniak et al., 2019; Dall'erba et al., 2021) for which travel time is a more suitable proxy than geometric distance since our context is a domestic setting where shipments by trucks are more prevalent,[12] and out-of-state farm-based agricultural shipments are assumed to be moved by trucks in the FAF (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 FAF's trade flow data which we use for the production of manufactured agrifood products. We undergo three steps for the variables in the second stage. First, data on aggregate production of food manufacturing is calculated from the FAF dataset. As for the 01–03 commodities, we begin by treating the FAF data by excluding any flows that are either imported or exported internationally. 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 value for each of the food commodities: animal feed (SCTG 04), meat/poultry preparations (SCTG 05), milled grains

[12] Details can be found here https://highways.dot.gov/public-roads/summer-2019/farm-table
While trucks are the dominant mode for shipping agricultural products, the major shipment type does differ by specific products. For instance, in 2016, 72% of corn, 51% of soybeans, and 29% of wheat was transported by trucks.

and bakery products (SCTG 06), other prepared foods (SCTG 07), alcoholic beverages (SCTG 08), and tobacco products (SCTG 09). Finally, we aggregate all the categories into a single food (SCTG 04–09) category by state and year to create the aggregated production of agrifood products.[13]

Second, for the data on labor, we use the total full-time and part-time employment for the two industries classified by the NAICS: food manufacturing (NAICS 311), and beverage and tobacco product manufacturing (NAICS 312). While the BEA provides annual observations for the 50 states from 1998 onward, some states are undisclosed, and the observations for 1997 are missing, which we deal with following the description in Appendix A.

Third, 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.[14] There are two sources for national capital stock: the Federal Reserve Board (FRB, 2023) and the National Bureau of Economic Research and U.S. Census Bureau's Center for Economic Studies Manufacturing Industry Database (NBER-CES) (Becker et al., 2021).[15] In our main empirical analysis, we use the national capital for the food, beverages and tobacco sector (NAICS 311 and 312) from the FRB (in 2012 U.S. dollars) after allocating it across states and years in proportion to the BEA value-added in food, beverages and tobacco manufacturing. We assume that all the states have the same capital-output (capital-labor) ratios in the manufacturing food and beverages industry because the ease of sector's capital mobility across states 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 values correspond 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

[13] 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 state capital.

[14] See other studies that allocate capital in the same manner (Peri, 2012; Yamarik, 2013; Han and Lee, 2016; Maestas et al., 2016).

[15] We use the national estimate of capital stock from the FRB because the NBER-CES data is missing the 2017 capital stock of food and beverages, thus requiring extrapolation. We apply the growth rate of the FRB stock from 2016 to 2017 and estimate the production function with the NBER-CES capital stock as robustness check.

Figure 1 displays the aggregate trends in total manufactured food and beverages production (a) and SPEI (b) over time. The low SPEI value in 2012 reflects the severity of the drought that struck most of the Midwest that year. Figure 2 displays the SPEI for commodities 01–03 for 2012 across states. If we focus on 02 commodities, it is clear in (b) that the 2012 drought was concentrated in the Midwest, more especially in Iowa, Illinois, and Nebraska, the major players in the production of cereal grains that accounted for 33.2% of the cereal grains traded within the United States (as of 2012 in terms of volume, calculated with data from the FAF, 2023). For commodities 01 and 03, the major producers experienced weaker drought conditions as mapped in (a) and (c) except for the soybean producers, Illinois and Iowa in (c), that accounted for 26.6% of the soybeans produced in the country (in 2012 in terms of bushels according to data from USDA NASS, 2023).

In the absence of trade and therefore no substitutable imports, drought-struck states would face a shortage of inputs and thus produce less agrifoods. However, there was a low rate of change in the production of manufactured food in 2012, showing that states maintained their 2007-level of agrifood output as seen in Figure 1 (a). Even with the SPEI having declined considerably in 2012 from the previous period, the total production of manufactured agrifood in the Midwest remained fairly constant in 2012 relative to the previous year. The same appears to hold true for California and Texas, where 18.5% of the total food and beverage manufacturing were produced (according to the 2012 data from the FAF, 2023), despite these states' dependence on the Midwest to source cereal grains, one of the primary crop products used as inputs for agrifood.

Figure 3 (a) depicts the total food and beverage manufacturing production (commodities 04–09) at the state level. California is a major producer with $173 billion of production on average for the sample period, followed by Texas ($100 billion), Illinois ($79 billion), and New York ($72 billion), as we would expect from states with a large population. However, there are significant differences in the way these states' production changes in response to extreme weather. When comparing 2007 to 2012, Figure 3 (b) shows that California experienced a slight decrease in food production even though it was not directly struck by the drought. Texas and Illinois experienced more severe drought, but both states were able to maintain a level of production similar to 2007. Whether the disruption in drought-struck states propagates to food manufacturing in distant states depends on the ability of the latter to purchase from alternative producers, the capacity of producers to adapt to dry conditions, and the availability of crop reserves from previous years.

Figure 4 displays, for each state, the change in locally produced grains (on the y-axis) and in imported cereal grains (on the x-axis) in 2012 compared to 2007. In addition, the dashed line indicates if a state had, overall, more grains available in 2012 (above the line) or less (below the line). States lie in one of the four planes depending on the direction of the change along the x- and y-axes: plane 1 includes 13 states that increase both local and imported grains, plane 3 with 13 states that reduce both, plane 2 where 8 states increase imports but decrease local inputs, and plane 4 where 14 states decrease imports but increase local inputs. Three observations stand out. First, we note a wide dispersion of states that experienced lower than -1 SPEI (as colored in red) and therefore had lower total 02 products available for use, especially in planes 2 and 3. States in plane 2 (e.g., Iowa, Illinois, Indiana, and Kansas) experienced local production losses that they compensated with imports from other states. States in plane 3 (e.g., Missouri and Ohio) seems to have been indirectly affected by production losses elsewhere: despite the considerable loss in local production, they reduced cereal grain imports too, thereby having less grains available in total (they are below the dashed line). Furthermore, we note that while California and Texas were moderately or almost not affected by drought, the states that these two states import grains from were clearly affected by severe drought. As it stands on the dashed line, Texas appears to have imported enough to mitigate the losses in 02 produced locally. How did it happen? The places sourcing Texas imports changed. In 2007, the top 4 states exporting to Texas were Kansas, Nebraska, Missouri, and Illinois. In 2012, grains from these states decreased by 82% (Nebraska), 83% (Missouri), and 90% (Illinois), respectively. As a result, Texas imported most from Kansas (207% increases compared to 2007), Oklahoma (+41%), and Louisiana (+15%) instead. We replicated this figure for SCTG 03, fruits and vegetables, in Appendix Figure C1. The figure shows a wide dispersion and a majority of states having more SCTG 03 commodities in 2012 than in 2007.

In short, being hit by a drought obliges a state to rely more heavily on imports of agricultural commodities, more especially when these are grains, fruits, and vegetables. Imports will originate from states that have experienced relatively less drought even when the latter are not the top producers of that commodity. The main reason is the need of the food and beverage manufacturing sector to maintain its historical level of production, even when a drought hits its home state. The ability to source more imports will depend on various factors, and thus differ by each state. Thus, the complex and diverging behavior of states in response to extreme weather, agricultural production and trade, and thus agrifood production downstream necessitates a systematic empirical analysis as reported in the next section.

4 Results

4.1 Gravity model estimates

Table 4 reports the estimates of equation (10). Columns 1–3 report the results estimated separately for each of the three agricultural commodity groups. The results display some notable features: First, we find evidence of a positive impact of a drought in the destination state on the imports of cereal grains from other states (as in column 2). In addition, the results indicate a significant and detrimental impact of a drought on the exports of cereal grains (as in column 2). The corresponding estimates for vegetables, fruits, and other agricultural products (SCTG 03) show the expected sign but they are not significant at 90%. These results confirm that local drought corresponds to a loss in productivity and therefore to a lesser volume available for exports but a higher volume needed as imports. The relationship is not necessarily one-to-one as states can rely on storage from the previous year. In addition, we hypothesize that, 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 trade in SCTG 01 (column 1), which we attribute to this category grouping a great variety of animals and fish and to the fact that a large amount of livestock raising takes place indoors where fans, misters and air conditioners are available (Schimmelpfennig et al., 1996).

Table 5 reports the estimates of equation (11) where we distinguish extreme from mild drought. Extreme drought is defined as the absolute value of SPEI below –1.3 and mild drought as the absolute value of SPEI between 0 and –1.3.[16] The classification for severe drought from the U.S. Drought Monitor is used for extreme drought in our case. The same threshold is used for wetness. The robustness checks with varying thresholds are presented in Appendix Figure D1. The results shown in Table 5 indicate that a 1% increase in the SPEI value of extreme drought in

[16] The threshold comes from https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx. We tried robustness checks with other threshold values, but the results are similar. Complete results are available in Appendix Figure D1.

the destination state increases the imports of SCTG 03 products by 0.652%. Another result to note in column 2 is that the negative impact of a drought on commodity SCTG 02 exports becomes larger compared to our previous specification. The estimates imply that a 1% increase in extreme drought (SPEI below –1.3) causes a 0.753% decrease in cereal grains exports. Similarly to the results in Table 4, our results with varying drought levels indicate that drought acts as a stronger pushing factor than pulling factor for the trade of cereal grains, while we find the opposite for SCTG 03 products. The Appendix Figure D2 shows that our results are robust to value as the dependent variable, two-way clustered standard errors, and alternative fixed effects and extreme weather measures.

Since we control for climate zone fixed effects, our findings capture how states engage in the trade of agricultural commodities to benefit from the differences between their own and their partners' comparative advantages. Yet, during selected years, origin and/or destination states experience short-run weather-induced disruptions which lead to changes in crop trade. This is in line with the results of the meta-analysis of Magalhães Vital et al. (2022) focusing on weather characteristics and trade of agricultural commodities.

4.2 Production function estimates

Table 6 reports the regression results for stage 2 after adopting the sum of the estimated value of the trade flows from stage 1 for the locally-sourced (intrastate) and imported inputs. Column 1 reports the coefficient estimate and standard error when we do not distinguish between extreme and mild drought in stage 1 while column 2 reports the corresponding figures when we split the two.

Panel A of Table 6 reports the NLS estimates of output elasticities and elasticities of substitution of each agricultural input group in equation (14).[17] The post-estimated marginal effects are also presented in Panel A.

The results displayed in columns 1 and 2 indicate that all the significant estimates of the distribution parameters are positive. Focusing on the results of column 1, we first find a significant output elasticity of approximately 0.200 for capital; whereas the elasticity of labor, at 0.591, is about 2.5 times larger. As expected, this suggests that labor serves as a more vital input for the production technology of the manufactured agrifood industry (as has been documented in

[17] For the NLS estimation, we used the "nl" command in Stata with predetermined initial values.

other contributions).[18]

Second, we find significant output elasticities for the crop input commodities. The estimates of SCTG 02 commodities show an output elasticity of 0.105 which is not statistically different from the elasticity of 0.128 for the SCTG 03 commodities. However, the elasticity of SCTG 01 commodities is not significant. We believe this is because livestock and fish products are not used across all SCTG 04–09 categories such as 04 (animal feed), 06 (milled grains, bakery), 08 and 09 (beverages and tobacco). Overall, our results confirm that food and beverage manufacturing is an input-intensive industry as demonstrated in the previous literature (Huang, 2003; Gandhi et al., 2020; Wahdat and Lusk, 2023).

Finally, our results reveal that locally-sourced and imported inputs are neither substitutes nor complements as indicated by the measured elasticities of substitution equal to one.[19] So, locally-produced and imported inputs are equally important for the production of food and beverage manufacturing as long as they are the same commodity. As such, a simple CD production function[20] would suffice to estimate the role of each input. Robustness checks based on this approach are reported in Table 6 Panel B. We attribute the lack of clear substitution or complementarity between locally grown and imported agricultural inputs to the fairly large number of commodities associated to each SCTG. For instance, SCTG 02 commodities alone include wheat, corn, rye, barley, oats, and rice and each of them matters to a different extent to the food manufacturing process of each of the SCTG 04 to 09 categories. As a result, current data allow us to perfectly measure substitution between local grains and imported grains but not between local and imported corn only. The same pitfall applies to SCTG 01 and 03 categories so that future research will offer a disaggregation at the product level. In addition, the heterogeneity in the states' trading behavior during extreme weather periods might affect these results (see Figure 4 in section 3.3, and Figure C1 in Appendix).

Ultimately, our findings emphasize that states do not prioritize local over imported inputs or inversely; instead, both inputs contribute to the production of manufactured food with

[18] Wahdat and Lusk (2023) measure a ratio of 5 for the U.S. agrifood industry. Although not in the United States, Gandhi et al. (2020) find that the ratio is 1.83 and 2.54 in Colombia and Chile, respectively.

[19] With the elasticity of substitution parameters that we estimated (as reported in Table 6 Panel A), we conduct the Wald test for the null hypothesis H_0: $\sigma_k = 1$ which is rejected at the 1% significance level for all the commodities.

[20] We impose another restriction when estimating the OLS marginal effects for the CD production function: the output elasticities of locally-sourced and imported inputs are the same within the same commodity group.

significantly positive productivity. More robustness checks with manufactured food as SCTG 04–07 commodities (i.e., excluding beverages and tobacco) and alternative capital stock measures are reported in Table E1 and E2 of the Appendix. They all confirm our findings. The rest of the analysis will rely on the marginal effects from NLS estimates (panel A) of elevated extreme drought (column 2) since they show the most consistent drought effects for both exports and imports of cereal grains (see Tables 4 and 5 in subsection 4.1).

4.3 Marginal impacts of drought on manufactured agrifood production

In order to examine further the heterogeneous, interstate, and intersectoral impacts of extreme weather events on agrifood manufacturing, this subsection offers several simulations. For each of them, the marginal impact of each origin-destination pair is captured in matrix (B3) of Appendix B. It encompasses three impacts: the intrastate effect on the diagonal (drought in j affects food production in j), the inward effect (drought in i affects food production in j), and the outward effect (drought in j affects food production in i). The first sub-section below illustrates this interstate and intersectoral spillover effect between California, Texas, and their trading partners since they are the top two producers in the domestic market of food manufacturing in the United States.[21] The analogous figures of simulations with vegetables, fruits, and other agricultural products (SCTG 03) are displayed in Appendix F.

4.3.1 Drought and bilateral spillovers from/to California and Texas

We start by simulating a 100% extreme drought increase on all the grain producing areas of California (CA) and Texas (TX) (substitution effect). Contrary to basic expectations, it leads to an increase in manufactured food and beverage production in each of the two states (compared to the 1997–2017 average production), as displayed in Figure 5. The key element is in the increase in cereal grains imported from other states, notably from the Midwest. The color code used in Figure 5 corresponds to the production losses CA (or TX) avoided by increasing imports from these origin states. The darker the color, the higher the avoided loss. For CA (Figure 5a), the mitigation effect is due to inputs imported from Nebraska ($2.48 billion) and Iowa ($1.22 billion). Together, they cover 68% of the total avoided loss, hence they represent key locations for CA's food manufacturing sector. When it comes to TX (Figure 5b), the agrifood production

[21] Estimates and standard errors of the marginal effects for other states are available from the authors upon request.

losses that are avoided are lower ($3.12 billion vs. $5.42 billion for CA) because the state's agrifood production is lesser ($100 billion vs. $173 billion) and its grain production is higher ($8.58 billion vs. $2.64 billion). As in the CA case, the states that mitigate the extreme weather effect in TX are located in the Midwest and are closer to the destination state. The key players are Kansas ($1.57 billion) and Missouri ($0.36 billion), the two states accounting for 62% of the total avoided loss.[22]

Figure 6 displays the production loss in CA (a) and TX (b) for another simulation, one by which we report the impact on these two states' food manufacturing following a homogenous 100% extreme drought increase on the grain producing areas of all the other states (inward effect). The color code corresponds to how much the destination state's agrifood manufacturing sees its production decrease following that event. The key providers this exercise reveals are the same as in the previous simulation. Yet, the final effect on agrifood production is now negative and the magnitude of the link is now greater, which reveals the latter simulation would be more devastating on the nation's agrifood supply chain than the previous one. For CA (Figure 6a), the food manufacturing losses would be large at $6.92 billion, $3.17 billion of which due to drought in Nebraska and $1.56 billion in Iowa. Similarly, in TX the losses are estimated at $3.99 billion, $2 billion of which due to drought-struck Kansas and $0.46 billion due to Missouri.[23]

The last bilateral simulation we report corresponds to how a 100% increase in extreme drought in the grain-producing areas of CA and TX lead to a loss in agrifood manufacturing in the rest of the nation (outward effect, Figure 7). Results indicate that an event striking CA would primarily affect Nevada ($167 million) and Iowa ($59 million) while the same event in TX would affect New Jersey ($385 million) and CA ($164 million). As expected, the bilateral outward effect is lower than the inward effect. The reason is that CA and TX are the nation's largest agrifood producers but they play a small role in growing cereal grains for the rest of the nation. We find a similar outcome for SCTG 03 in Appendix Figure F3.

4.3.2 Drought and nation-wide impacts

[22] A similar exercise for vegetables, fruits, and other agricultural inputs (SCTG 03) is offered in Appendix Figure F1. Results show that for CA (total loss is $7.5 billion), the key providers are Arizona and Oregon; for TX (total loss is $4.32 billion) they are Nebraska along with Oklahoma and Louisiana. As expected, the key links in the agricultural trade network vary by commodity type.

[23] The results of a similar exercise for SCTG 03 are reported in Appendix Figure F2. The key players are the same as in Figure F1 and we note that, again, the reported loss ($1.37 billion in CA and $0.79 billion in TX) is less than the one due to a drought on grain producing areas (Figure 6).

While the heterogeneity in the state-level effects depicted above allow us to uncover the key trade linkages in SCTG 02 and 03 commodities, they lack information on which agrifood manufacturing state benefits (or loses) the most from engaging in trade. We thus expand the previous three simulations to the national level. For instance, in Figure 8 we report, in the event of a 100% increase in local extreme drought, how much agrifood loss is avoided by increasing imports of grains from other states. We note for CA and TX the amounts of $5.42 billion and $3.12 billion respectively that were already presented in Figure 5. The other high-impacted states are in the Midwest, the North-East and South-East whereas the states that would experience lesser losses are along the Colorado Rockies and on the Western part of the nation (except CA). Appendix Figure F4 shows the matching map for SCTG 03.

Figure 9 expands the simulation done in Figure 6. It shows that the nation's agrifood production is the most sensitive to droughts in midwestern states, the large grain producers. The largest loss would originate from a severe drought in Nebraska ($6.60 billion), Indiana ($5.52 billion), or Illinois ($4.72 billion). A similar exercise for SCTG 03 commodities is reported in Appendix Figure F5. We discover that agrifood manufacturing would primarily suffer from a drought taking place in the West, South, and the Corn Belt, particularly in Nebraska, Kansas, Illinois, and Iowa. While the surprise is that these states are not particularly known for fruits and vegetables production, the explanation lies in soybean production, the "other agricultural products" part of SCTG 03, a commodity of which 70% goes to animal feed production, one of the components of the nation's agrifood manufacturing sector.

Finally, Figure 10 shows the distribution of the agrifood production losses that would result from extreme drought occurring in the rest-of-the-country. CA is the state suffering the most from a drought occurring in the grain producing areas of the other states ($6.92 billion). It is closely followed by TX at $3.99 billion. This reflects how CA and TX are "key" players in the nation's food manufacturing sector (see Figure 3a) and are highly dependent on inflows of cereal grains (much more than of SCTG 03 commodities, as reported in Appendix Figure F6). The next most vulnerable state is Illinois followed by New York and Pennsylvania, as explained by their high population and thus high demand of final food products compared to other states.

5 Conclusion

The growing U.S. population and the increasing occurrence of extreme weather events oblige us to better understand the impact of a changing climate on the food supply chain of the nation. This paper tackles this crucial relationship through a novel two-stage approach that allows us to account for both interstate and intersectoral spillovers 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.

Our empirical approach and set of results can be summarized as follows. In the first stage, we rely on a gravity model of trade to measure how extreme weather events affect the bilateral trade flows of three types of agricultural inputs conditional on other factors including climate zones. We then apply a nested production function of the food manufacturing sector to identify the effect of labor, capital, and aggregated agricultural inputs while allowing a constant elasticity substitution between local and imported inputs. Three important results emerge from our estimates. First, we confirm the findings of Dall'erba et al. (2021) that drought reduces exports of cereal grains while, inversely, drought at destination obliges the states to increase their imports of cereal grains as well as the rest of the crops (including vegetables, fruits, soybeans, oilseeds, and other agricultural products). This is because they need to carry on with their agrifood manufacturing activities, including animal feed, and previous year's storage does not always suffice. In sum, the domestic trade network exacerbates, and at the same time, mitigates the impact of weather extremes on food production and availability. Second, while stage 2 results confirm that the productivity of intermediate crop inputs (grains, vegetables, fruits, and others) is positive, states do not treat local and imported inputs as either substitutes or complements. Instead, all agricultural commodities are necessary inputs in the food manufacturing process so that a CD production function would have sufficed to estimate the role of each input.

The third, and eventually the most visually explicit of our results, is our detection of the key origin-destination linkages for the largest players in the domestic food supply chain of the country. California and Texas, the two largest agrifood manufacturing states in the country, are very dependent on grains from several Midwestern and Central states, much more than on other agricultural commodities such as fruits and vegetables, grown in other locations. As a result, the national agrifood supply chain is particularly vulnerable to weather shocks in these locations. At the same time, climate change is pushing these locations to experience a slow but certain drift in their agricultural specialization so the challenge of feeding a growing population will certainly be met by agrifood companies shifting to new locations, more northward and closer to the Rockies, for their agricultural inputs (McCarl et al., 2016; Cho and McCarl, 2017).

This work could be extended in various directions, including an analysis by transportation mode as the availability of the rail and water network varies by location and segments. Another extension would consist in disaggregating trade flows to the commodity level, as Smith et al. (2017) have done it for corn, but while accounting for the role of extreme weather events, drought and wetness like we have done here, and extending it to other events such as early frost and hail.

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Tables and Figures

Table 1. SCTG 01–03 products used as inputs for SCTG 04–09

(a) Before rescaling

	SCTG									House-hold 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 ratios above 2% for SCTG 04–09

	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

Note: The values in (a) report the amount of SCTG 01–03 used per $1 of production of SCTG 01–09 based on the national Input-Output table. Sum column on the right shows the sum of shares above 2% used for SCTG 04–09. The values in (b) show the amount of SCTG 01–03 used per $1 of production of manufactured food, SCTG 04–09 with ratios above 2%. *Source*: Authors' construction with data from the Input-Output table (IMPLAN, 2020).

Table 2. Description of the variables used in the gravity model (Eq. 11)

Variable	Description	Source
Trade flows of agricultural commodity 01–03	Volume of trade flows between the origin and destination state (1,000 tons)	FAF
Drought	Absolute value of SPEI < 0 in each state	ERA5-Land
Wetness	Value of SPEI > 0 in each state	ERA5-Land
Agricultural production	Total output of agricultural commodity 01–03 in the origin state (2012 U.S.$)	FAF
Food production	Value-added of food, beverages and tobacco manufacturing industry in the destination state (2012 U.S.$)	BEA
Growing degree days (GDD)	Temperature as measured in growing degree days during the growing season in farmland	ERA5-Land
Precipitation	Precipitation during the growing season in farmland (mm)	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 used in the production function (Eq. 14)

Variable	Description	Source
Production of food and beverages manufacturing	Sum of traded manufactured food products (SCTG 04–09) leaving the state representing total output of manufactured food in 2012 U.S. $	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 allocated by share of state-level value-added in 2012 U.S. $	FRB, BEA
Local animals and fish (01)	Predicted intrastate flow of animals and fish (01)	Gravity model
Imported animals and fish (01)	Sum of all predicted interstate flows of animals and fish (01)	Gravity model
Local cereal grains (02)	Predicted intrastate flow of cereal grains (02)	Gravity model
Imported cereal grains (02)	Sum of all predicted interstate flows of cereal grains (02)	Gravity model
Local vegetables, fruits, and other agricultural products (03)	Predicted intrastate flow of vegetables, fruits, and other agricultural products (03)	Gravity model
Imported vegetables, fruits, and other agricultural products (03)	Sum of all predicted interstate flows of vegetables, fruits, and other agricultural products (03)	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)
Agricultural production_orig.	0.747***	(0.115)	0.592***	(0.086)	0.448***	(0.068)
Food production_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: Dependent variable is the volume of trade flows. 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)
Agricultural production_orig.	0.746***	(0.115)	0.590***	(0.086)	0.448***	(0.068)
Food production_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	

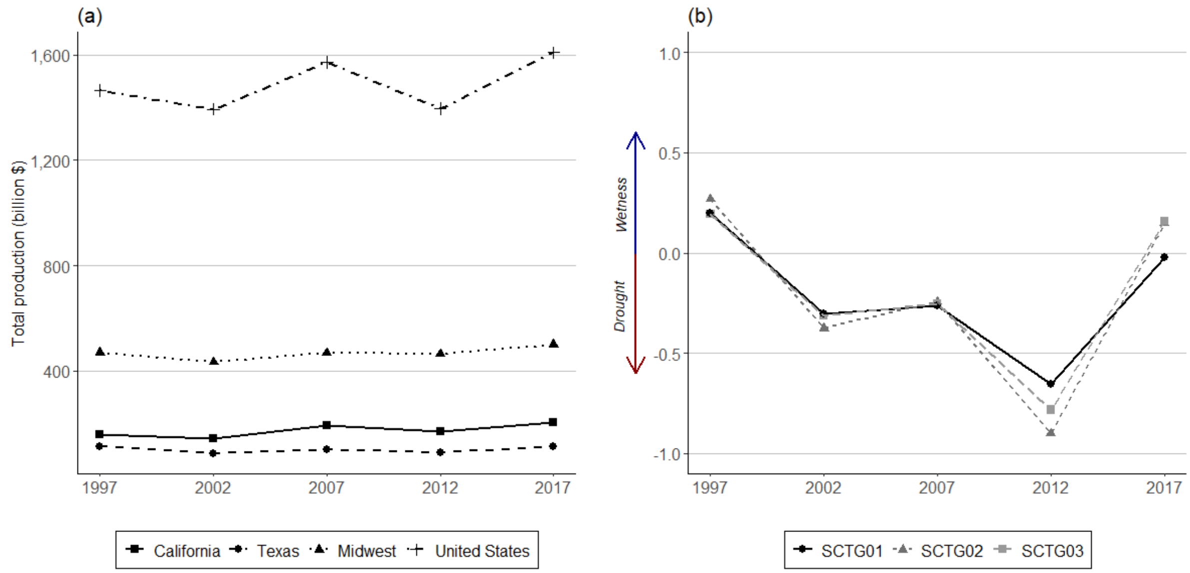
Note: Dependent variable is the volume of trade flows. Standard errors are clustered by state pairs and are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. All estimations include state-pair, exporter climate zone-year, and importer climate zone-year fixed effects. MRTs for distance, 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

	With drought (1)		With extreme/mild drought (2)	
	Coefficient	Std. Error	Coefficient	Std. Error
Panel A. NLS estimates				
Output elasticities				
Capital	0.200**	(0.091)	0.199**	(0.091)
Labor	0.591***	(0.120)	0.586***	(0.124)
Animals and fish (01)	–0.024	(0.033)	–0.025	(0.032)
Cereal grains (02)	0.105**	(0.049)	0.106**	(0.045)
Vegetables, fruits, and other (03)	0.128*	(0.078)	0.133*	(0.081)
Elasticities of substitution				
Animals and fish (01)	0.343	(8.174)	0.319	(6.956)
Cereal grains (02)	0.747	(5.475)	0.745	(8.748)
Vegetables, fruits, and other (03)	1.175	(15.326)	1.180	(18.504)
Marginal effects				
Animals and fish (01)	–0.012	(0.017)	–0.012	(0.016)
Cereal grains (02)	0.053**	(0.025)	0.053**	(0.023)
Vegetables, fruits, and other (03)	0.064*	(0.039)	0.067*	(0.041)
Panel B. OLS estimates				
Output elasticities (marginal effects)				
Capital	0.196**	(0.095)	0.195**	(0.095)
Labor	0.594***	(0.144)	0.590***	(0.145)
Animals and fish (01)	–0.005	(0.014)	–0.006	(0.014)
Cereal grains (02)	0.057**	(0.027)	0.057**	(0.027)
Vegetables, fruits, and other (03)	0.054	(0.051)	0.056	(0.053)
Observations	240	240	240	240

Note: Dependent variable is the value of food and beverage manufacturing. Standard errors are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Column 1 shows coefficients that include agricultural input variables estimated from the gravity model with drought. Column 2 shows results when including agricultural input variables estimated with extreme/mild drought. Panel A reports the nonlinear least squares (NLS) estimators with state and year dummies of equation (14). Each column of Panel A reports the parameter estimates and the marginal effects ($\frac{\gamma}{2}$) of locally grown and imported inputs of each commodity SCTG 01–03. The NLS standard errors are bootstrapped based on 200 replications clustered at the state level. Panel B reports the ordinary least squares (OLS) estimators with state and year fixed effects, and the standard errors are clustered at the state level.

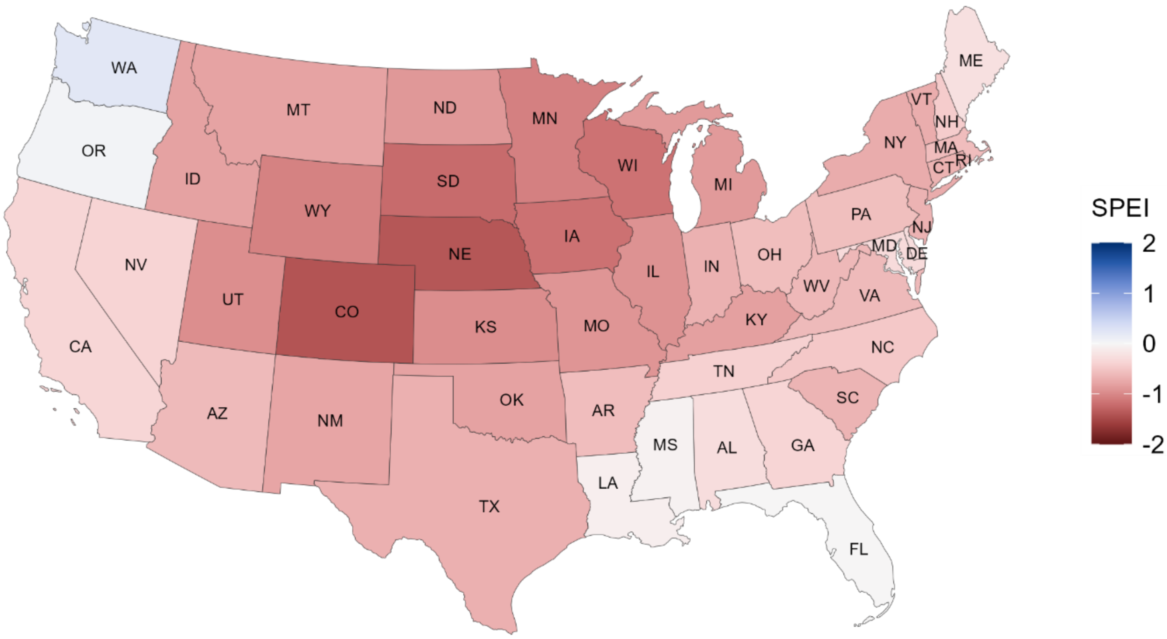
Figure 1. Manufactured food and beverages production and drought/wetness, 1997–2017



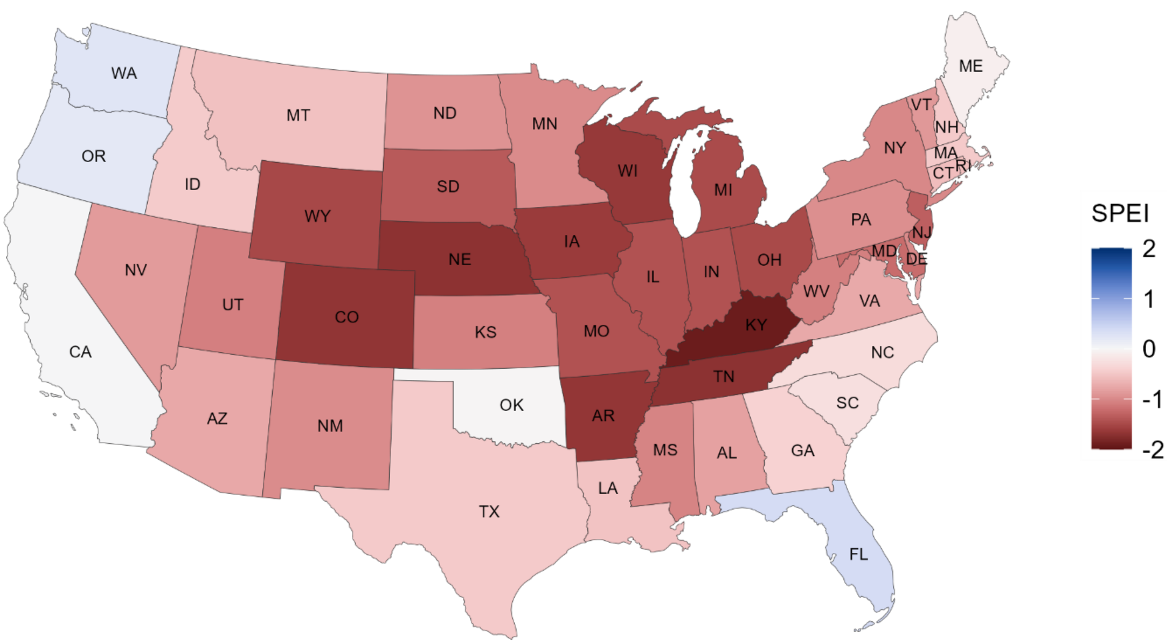
Note: Panel (a) shows the total production of manufactured food production by region. The values of production are in 2012 dollars and are calculated as the sum of all the outflows, intrastate and interstate, to U.S. states in sectors SCTG 04–09. Panel (b) shows the national average of the state-level SPEI by agricultural commodity. Negative (or positive) SPEI indicates drought (or wetness). *Source*: Authors' construction with data from FAF (2023) and ERA5-Land (Muñoz Sabater, 2019).

Figure 2. SPEI by commodity and state, 2012

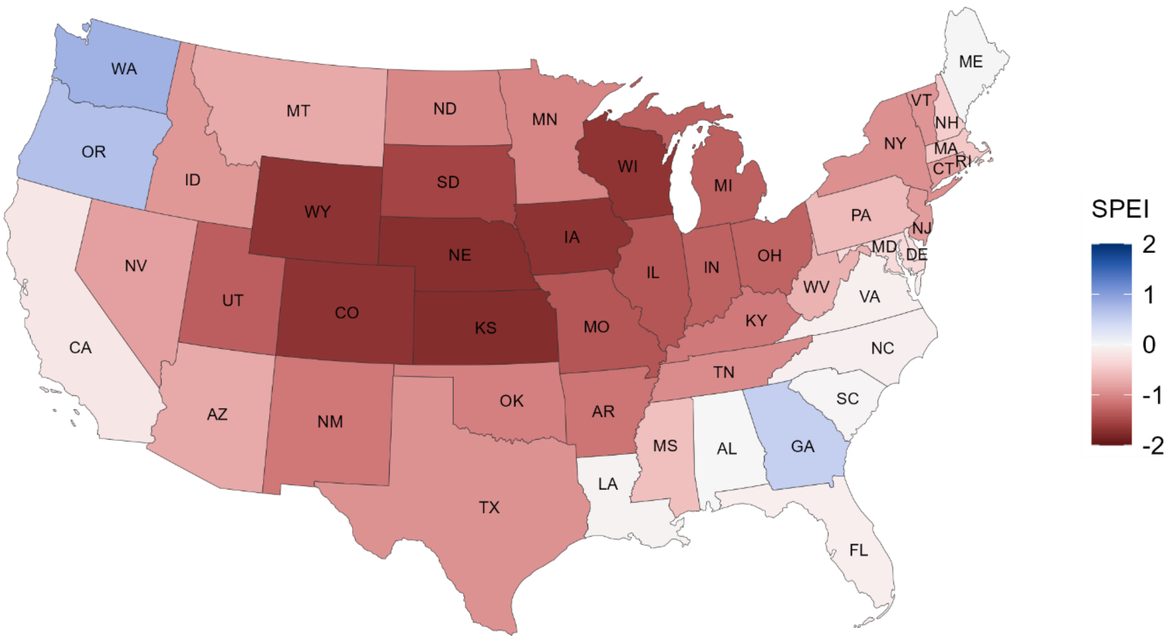
(a)



(b)

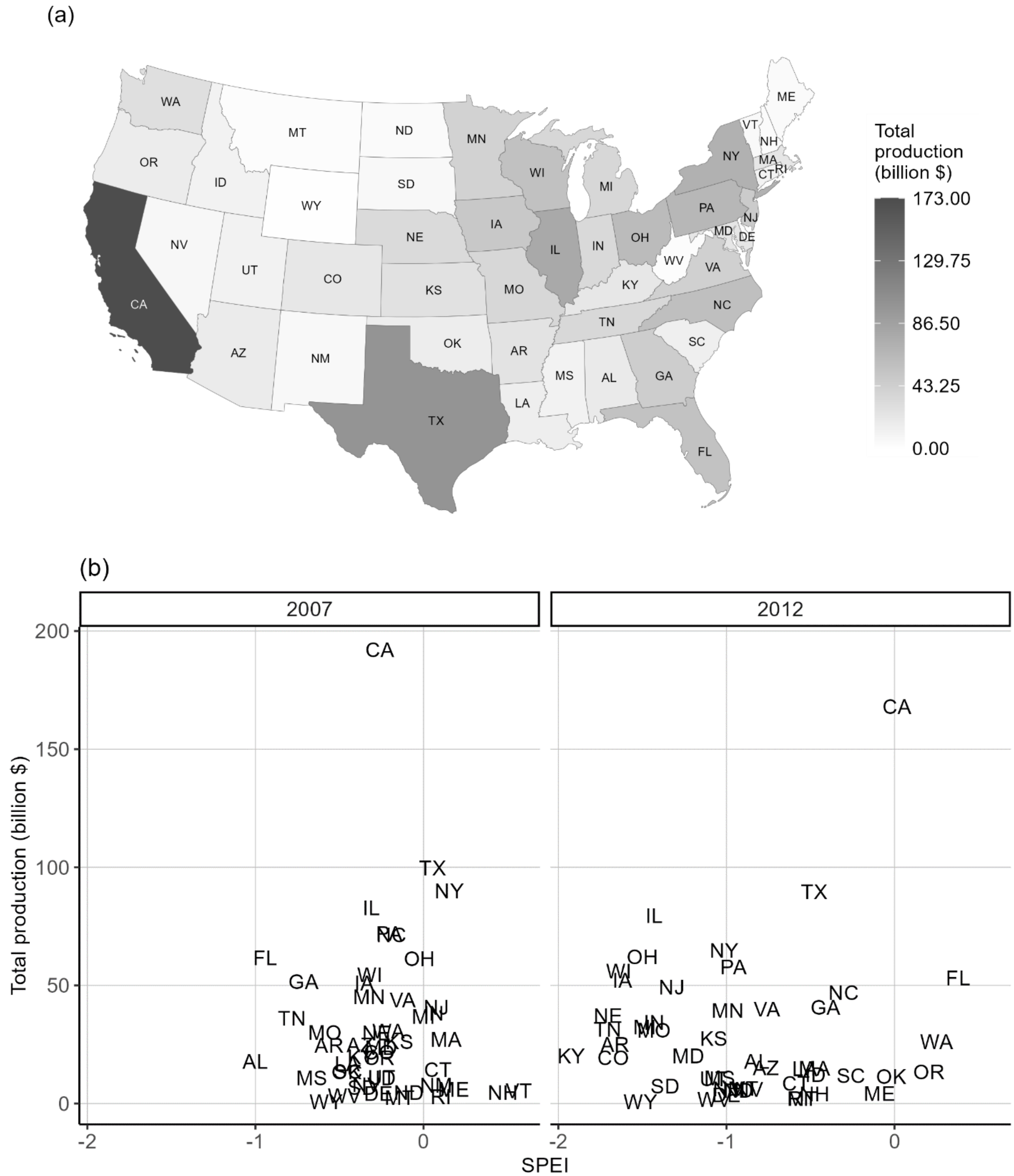


(c)



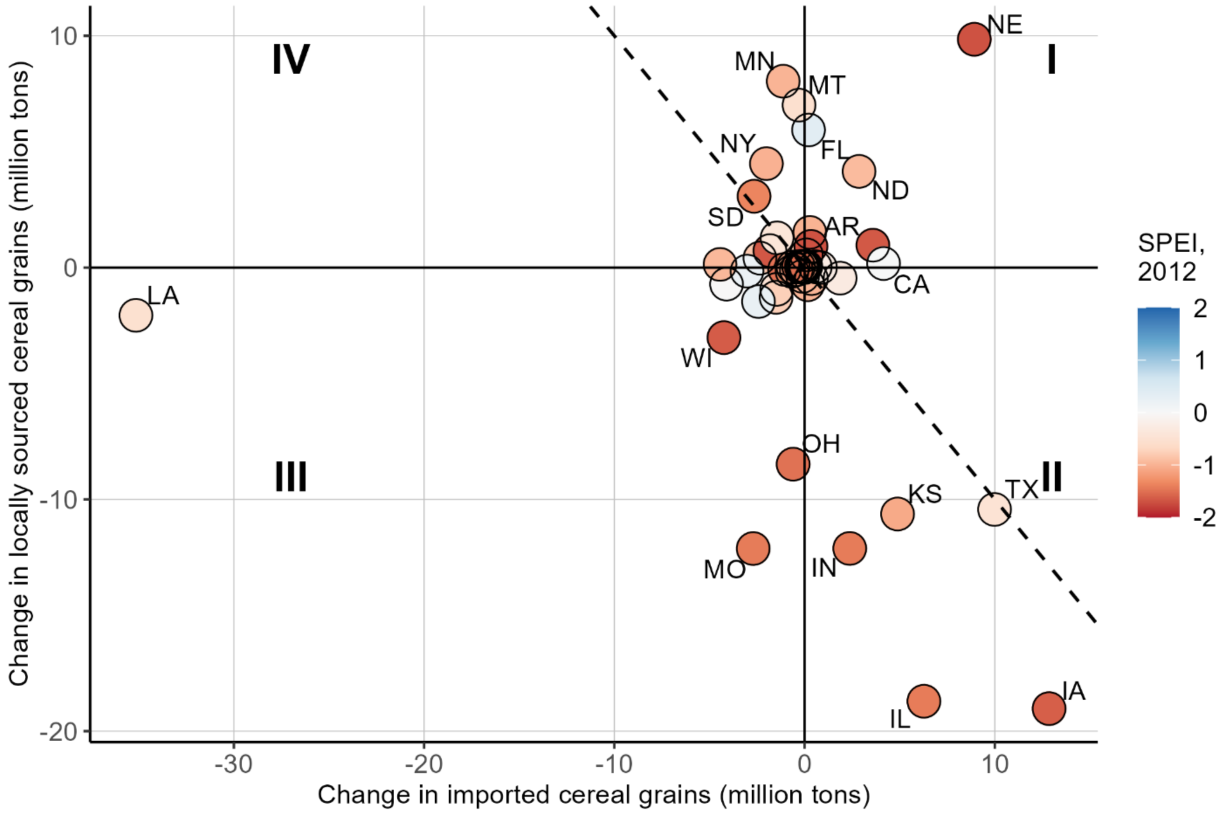
Note: The map shows the SPEI by commodity and state in 2012. State-level SPEIs are the aggregated county-level measures weighted by commodity 01 sales (a), commodity 02 farmland (b), and commodity 03 farmland (c). Negative (red) values indicate drought, and positive (blue) values indicate wetness. *Source*: Authors' construction with data from ERA5-Land (Muñoz Sabater, 2019).

Figure 3. Total production of manufactured food and SPEI



Note: Panel (a) shows the total production of food and beverage manufacturing as average 1997–2017. Panel (b) shows the scatter plot of the total production of food manufacturing (y-axis) and SPEI (x-axis) for 2007 and 2012. Total production is calculated as the total intrastate and interstates outflows to U.S. states of manufactured agrifood commodities 04–09 for each state. All the production values are in 2012 dollars.

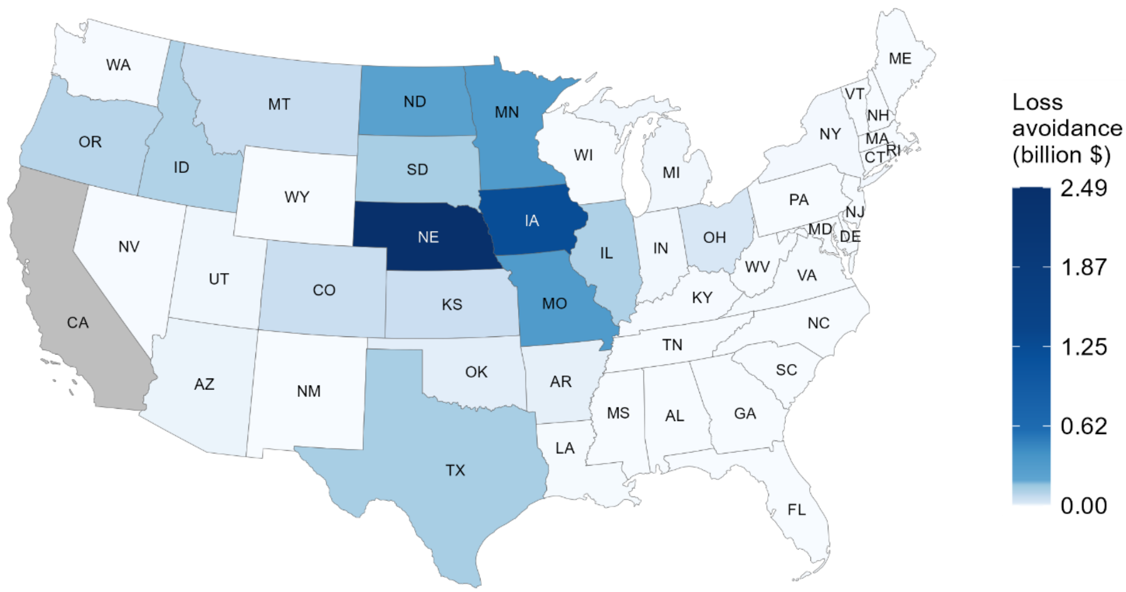
Figure 4. Relationship between locally sourced and imported cereal grains, change over 2007–2012



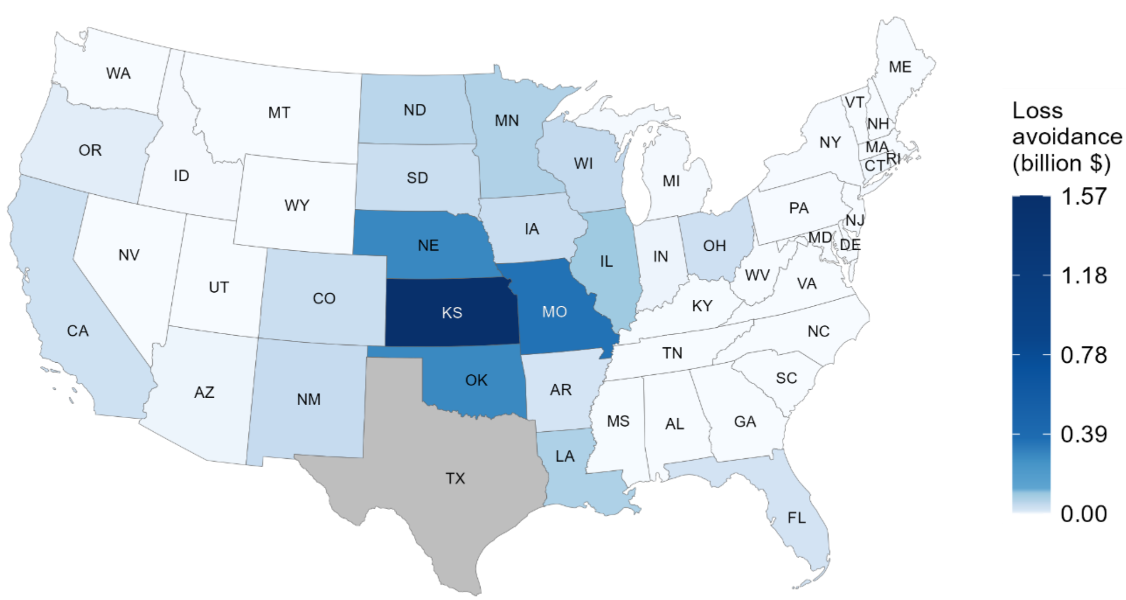
Note: Scatter plot of the change in volume of locally sourced cereal grains (y-axis) and imported cereal grains (x-axis) from 2007 to 2012 in million tons. The colors of the points represent the SPEI in 2012 where negative (red) values indicate drought and positive (blue) values wetness. States above the y=–x (dashed) line have more available 02 products relative to 2007, and states below it have less products. The same figure for commodity 03 is in Appendix C. *Source*: Authors' construction with data from FAF (2023) and ERA5-Land (Muñoz Sabater, 2019).

Figure 5. Loss avoidance in the food and beverages manufacturing production of California (a) and Texas (b) following a 100% drought increase in California and Texas (gray) and a shift in the places of import (colored)

(a)



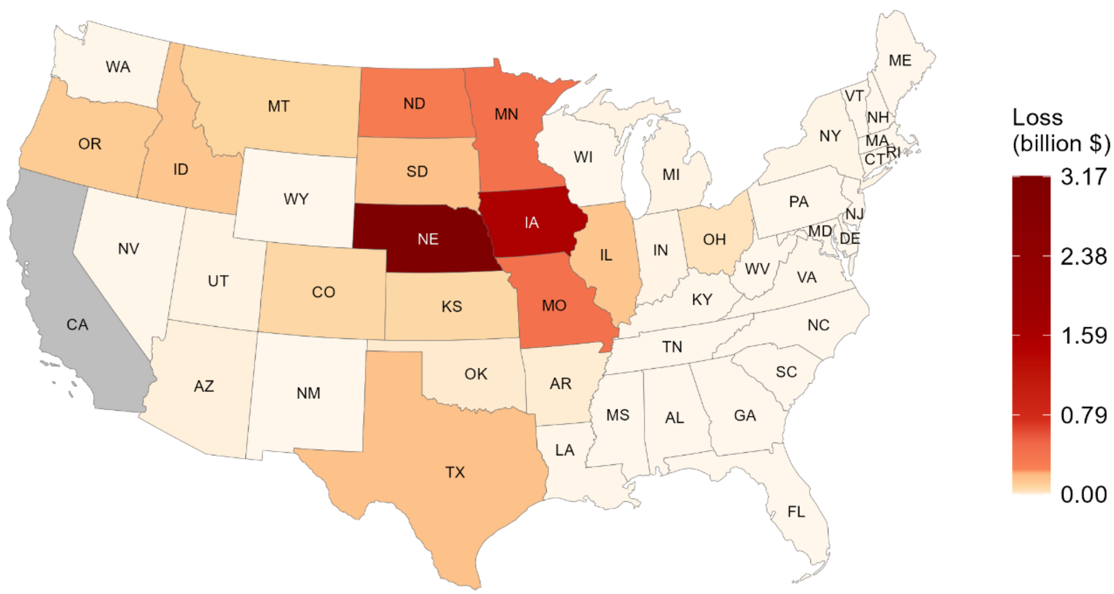
(b)



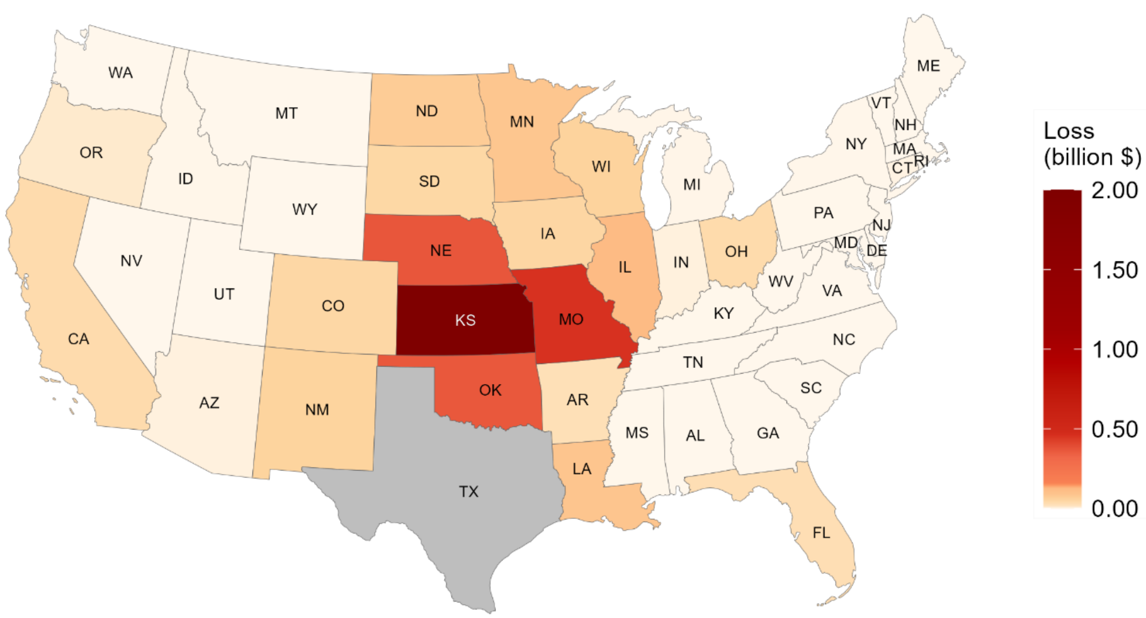
Note: Each impact is estimated as $\frac{\gamma\alpha^D}{2}\cdot\frac{I_{i,CA}}{M_{CA}}\cdot Y_{CA}$ for California. Estimates and standard errors are reported in Appendix G. The same figures for vegetables, fruits and other agricultural products are reported in Appendix F.

Figure 6. Loss in the food and beverages manufacturing production of California (a) and Texas (b) following a 100% drought increase in the State of origin (colored)

(a)



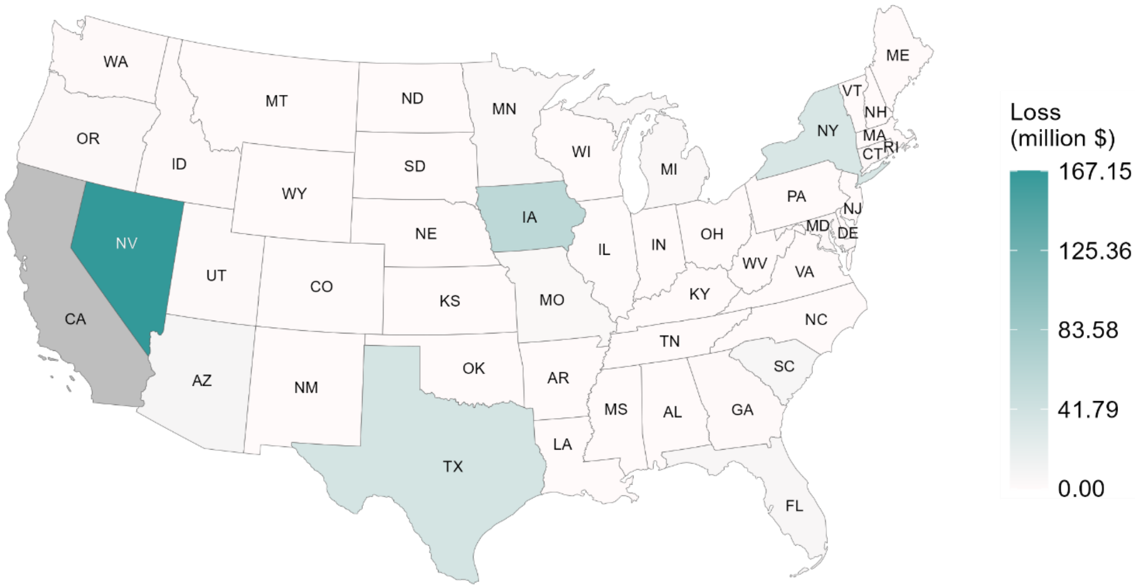
(b)



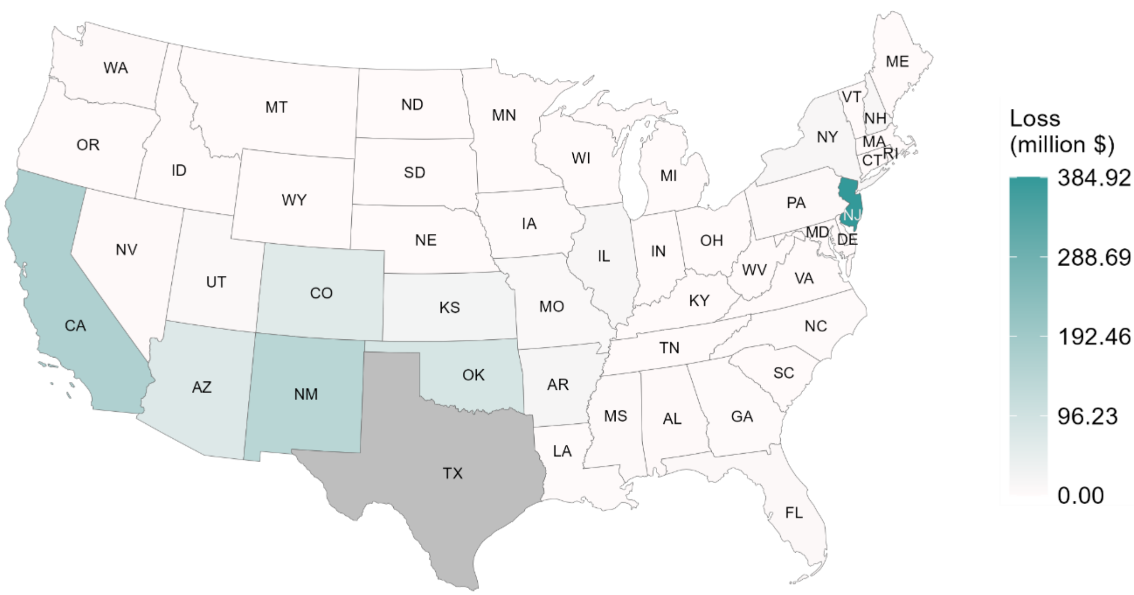
Note: Each impact is calculated as $\frac{\gamma\alpha^O}{2}\cdot\frac{I_{i,CA}}{M_{CA}}\cdot Y_{CA}$ for California. Estimates and standard errors are reported in Appendix G. The same figures for vegetables, fruits and other agricultural products are reported in Appendix F.

Figure 7. Loss in the food and beverages manufacturing production in the State of destination (colored) following a 100% drought increase in California (a) and Texas (b)

(a)

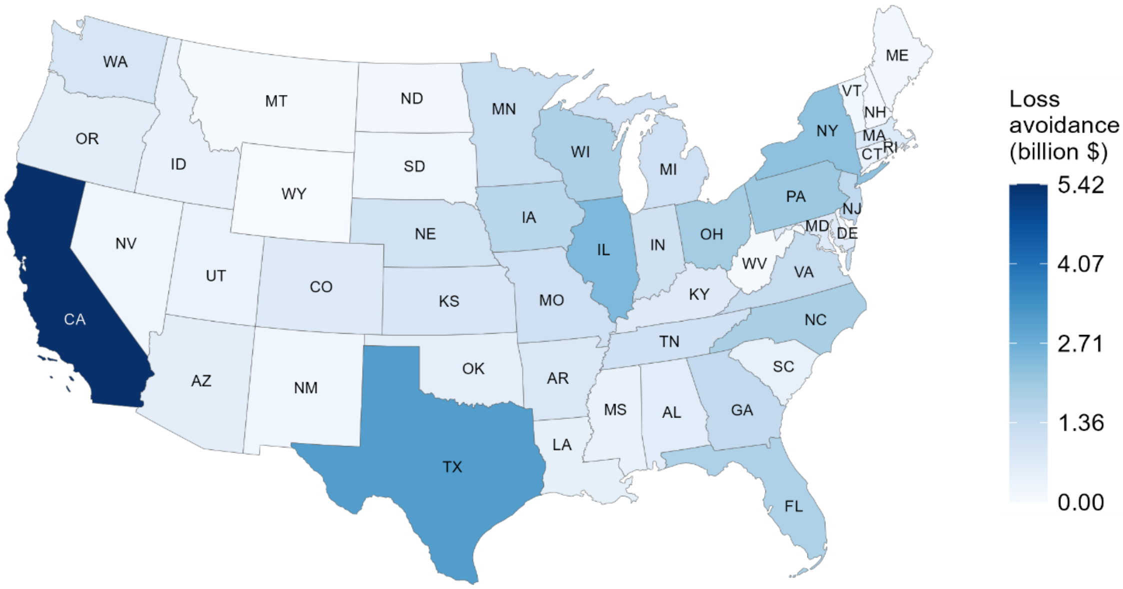


(b)



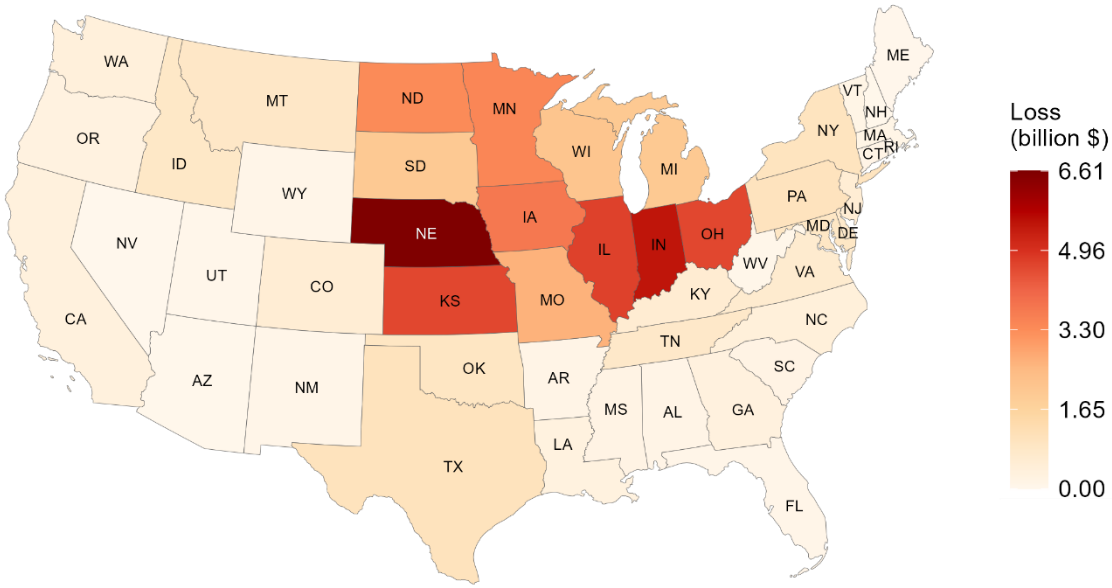
Note: Each impact is calculated as $\frac{\gamma\alpha^{O}}{2} \cdot \frac{I_{CA,j}}{M_j} \cdot Y_j$ for California. Estimates and standard errors are reported in Appendix G. The same figures for vegetables, fruits and other agricultural products are reported in Appendix F.

Figure 8. Sum of avoided losses in the food and beverages manufacturing production of each state (colored)



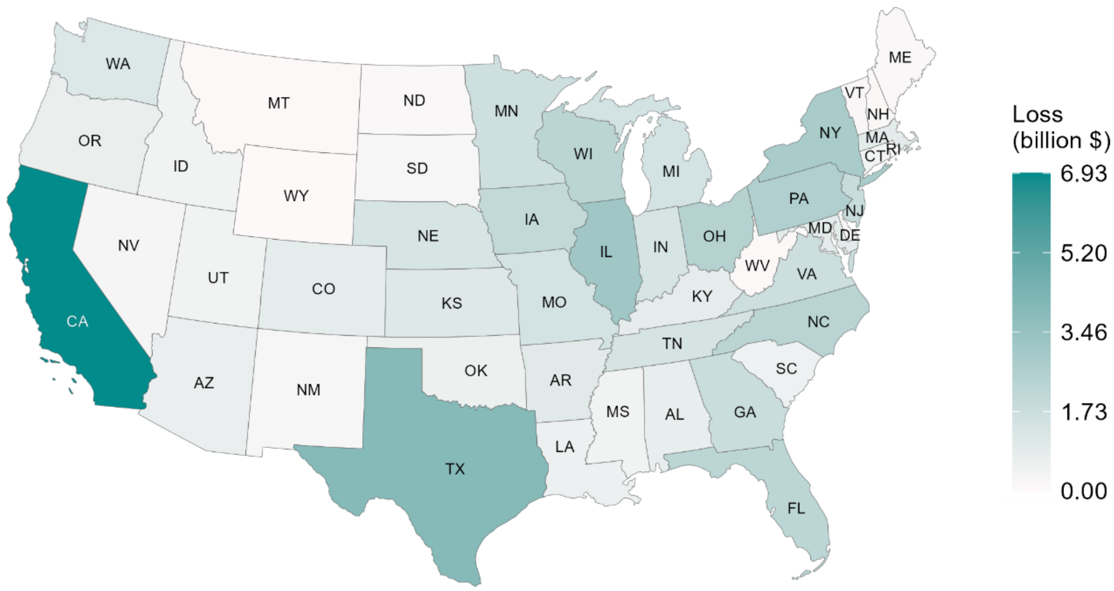
Note: The loss comes from a 100% increase in local drought (colored states) and is avoided by importing cereal grains from the rest of the nation. Each impact for state j is calculated as $\frac{\gamma\alpha^D}{2} \cdot Y_j$. Estimates and standard errors are reported in Appendix G. The same figure for vegetables, fruits, and other agricultural products are reported in Appendix F.

Figure 9. Sum of food and beverage manufacturing production losses in the rest of the nation following a 100% drought increase in the State of origin (colored)



Note: Each impact state j is calculated as $\frac{\gamma\alpha^{O}}{2}\cdot Y_j$. Estimates and standard errors are reported in Appendix G. The same figure for vegetables, fruits, and other agricultural products are reported in Appendix F.

Figure 10. Food and beverage manufacturing production loss in the State of destination (colored) following a 100% drought increase in the rest of the nation



Note: Each impact state j is calculated as $\frac{\gamma\alpha^{O}}{2}\sum_{i}^{n}(\frac{I_{ji}}{M_i}\cdot Y_i)$. Estimates and standard errors are reported in Appendix G. The same figure for vegetables, fruits, and other agricultural products are reported in Appendix F.

Appendix A. Construction of labor data

The data on labor is provided for each of the two manufacturing industries: food manufacturing (NAICS 311), and beverage and tobacco manufacturing (NAICS 312). Several challenges emerged when constructing the state level labor data, especially for NAICS 312. Undisclosed data is one even if the undisclosed values for labor can be easily recovered for some states (e.g., South Dakota and Vermont) from taking the difference between the total values of the upper regions and the sum of the rest.[1] In the event where more than one state reports a missing observation, we use the rate of the state's employment in the upper region's value from previous years for which both values are recorded.[2] After taking the average of the rate for all observable years, we apply the average rate to the years with the missing values. This approach assumes that the proportion of employment within the beverage 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 from the Standard Industrial Classification (SIC) to the North American Industry Classification System (NAICS) following the approach of Peri (2012). The concordance report is from the U.S. Census Bureau,[3] and employment for the SIC industries in 1997 is from the BEA. In the concordance, number of employees that are mapped to the corresponding NAICS industry are listed for each SIC industry. We first calculate the percentage of each SIC industry's number of employees that belong to food manufacturing (NAICS 311) and beverage and tobacco manufacturing (NAICS 312) out of the total number of employees for each SIC industry. We then map each SIC agrifood industry's value added from the BEA to NAICS 311 and NAICS 312 using the rate calculated with the SIC-NAICS concordance.[4]

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[1] The upper region for South Dakota is the Plains, and for Vermont is 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 NAICS 312 are food and kindred products (SIC 20), tobacco products (SIC 21), 1.56% of food stores (SIC 54) and 0.05% of wholesale trade (SIC 50-51). For Delaware and Nevada, employment for tobacco products (SIC 21) is missing so for these states we use the average of the nearest three years.

Appendix B. Marginal effect of local and imported inputs

Assuming one input group as in equation (B1), the marginal effect (or output elasticity) of local input I on food production Y is equation (B2):

$$Y = (PT)L^{(1-\beta-\gamma)}K^{\beta}\left(\left[I^{\frac{\sigma-1}{\sigma}} + M^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}\right)^{\gamma}, \tag{B1}$$

$$\frac{d\ln Y}{d\ln I} = (1-\beta-\gamma)\cdot\frac{d\ln L}{d\ln I} + \beta\cdot\frac{d\ln K}{d\ln I} + \gamma\cdot\frac{I^{\frac{\sigma-1}{\sigma}}}{I^{\frac{\sigma-1}{\sigma}} + M^{\frac{\sigma-1}{\sigma}}} + \gamma\cdot\frac{M^{\frac{\sigma-1}{\sigma}}}{I^{\frac{\sigma-1}{\sigma}} + M^{\frac{\sigma-1}{\sigma}}}\frac{d\ln M}{d\ln I}. \tag{B2}$$

In equation (B2), L is labor, I is locally-sourced 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 elasticity of substitution. With $\frac{d\ln L}{d\ln I} = 0$, $\frac{d\ln K}{d\ln I} = 0$, and $\sigma = 1$ (as estimated in NLS regression), the direct marginal effect is $\frac{\gamma}{2}$. If we account for indirect effects through a change in imported inputs ($\frac{d\ln M}{d\ln I}$), we also include the fourth term as the marginal effect of local inputs. The 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). As a result, the elasticity of substitution σ is not the same as $\frac{d\ln M}{d\ln I}$. However, since $\sigma = 1$, we assume that $\frac{d\ln M}{d\ln I} = 0$. We will report the (direct) marginal effect for now.

Equation (B2) gives the marginal effect of the locally grown input on manufactured food production, which constitutes the second stage of our analysis. The marginal effect of the imported input on manufactured food ($\frac{d\ln Y}{d\ln M}$) will just be identical to equation (B2) with all I now corresponding to M. As discussed above, the direct marginal effect of local (imported) inputs will be $\frac{\gamma}{2}$ ($=\frac{d\ln Y}{d\ln I} = \frac{d\ln Y}{d\ln M}$) based on our estimated parameter $\sigma = 1$. We need the derivative of manufactured agri-food production with respect to drought (our exogenous extreme weather shock). Equation (B3) is the full matrix derivative of manufactured food production. The diagonal elements are the intrastate effects which are expressed in greater detail in equation (B4). The first term of equation (B4) is the change in manufactured food production through changes in locally produced input, I_{jk}, called the *local input channel*. The second term is the change in manufactured food production Y_j that occurs through changes of imported inputs, M_{jk} , which we refer to as the *imported input channel*. Equation (B5) represents the effect with our evaluated estimates from the main analysis, where $\sum_{i\neq j}^{48} I_{ijk} = M_{jk}$ 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 sum of the shares of origin states i that state j imports from equals 1, which leads to (B6) where the parameter γ_k is the output elasticity of aggregate input k. Tests for the null $\sigma = 1$ cannot be rejected in our evaluation for the parameter, thus we divide γ_k by two which gives us the same *local input channel* and *imported input channel* ($\frac{I^{\frac{\sigma-1}{\sigma}}}{I^{\frac{\sigma-1}{\sigma}}+M^{\frac{\sigma-1}{\sigma}}} = \frac{M^{\frac{\sigma-1}{\sigma}}}{I^{\frac{\sigma-1}{\sigma}}+M^{\frac{\sigma-1}{\sigma}}} = \frac{1}{2}$).

$$\frac{\partial \mathbf{lnY}}{\partial \mathbf{lnD_k}} = \begin{bmatrix} \frac{\partial \ln Y_1}{\partial \ln D_{1k}} & \cdots & \frac{\partial \ln Y_1}{\partial \ln D_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \ln Y_n}{\partial \ln D_{1k}} & \cdots & \frac{\partial \ln Y_n}{\partial \ln D_{nk}} \end{bmatrix}, \tag{B3}$$

$$\frac{\partial \ln Y_j}{\partial \ln D_{jk}} = \frac{\partial \ln Y_j}{\partial \ln I_{jk}} \frac{\partial \ln I_{jk}}{\partial \ln D_{jk}} + \frac{\partial \ln Y_j}{\partial \ln M_{jk}} \frac{\partial \ln M_{jk}}{\partial \ln D_{jk}}, \tag{B4}$$

$$\frac{\partial \ln Y_j}{\partial \ln D_{jk}} = \frac{\gamma_k}{2} \cdot \alpha_k^H + \frac{\gamma_k}{2} \cdot \alpha_k^D \sum_{i\neq j}^{n} \frac{I_{ijk}}{M_{jk}}, \tag{B5}$$

$$\frac{\partial \ln Y_j}{\partial \ln D_{jk}} = \frac{\gamma_k}{2} \cdot \alpha_k^H + \frac{\gamma_k}{2} \cdot \alpha_k^D \tag{B6}$$

The off-diagonal row elements of the derivative matrix (B3) are the inward effects. The inward effect is the change in local (destination) manufactured agri-food production induced from an increase in drought taking place in other origin states which is decomposed further in equation (B7).

In equation (B7), the local channel for the inward effect ($\frac{\partial \ln Y_j}{\partial \ln I_{jk}} \frac{\partial \ln I_{jk}}{\partial \ln D_{ik}}$) pertains to the increase/decrease in locally produced agricultural inputs induced by drought in other trading states.

It can occur through changes in multilateral resistance components. We set this term 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 first-order drought impact is the second term. The inward effect is thus represented as equation (B8) with only the second term of equation (B7) and the estimated parameters. 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 given in equation (B9). Here, the sum of the trade flow ratio is also equal to one leaving us with the marginal effects given in equation (B10).

$$\frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\partial \ln Y_j}{\partial \ln I_{jk}} \frac{\partial \ln I_{jk}}{\partial \ln D_{ik}} + \frac{\partial \ln Y_j}{\partial \ln M_{jk}} \frac{\partial \ln M_{jk}}{\partial \ln D_{ik}}, \tag{B7}$$

$$\frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_k^O \cdot \frac{I_{ijk}}{M_{jk}}, \tag{B8}$$

$$\sum_i^n \frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_k^O \sum_i^n \frac{I_{ijk}}{M_{jk}} \quad \forall\, i \neq j, \tag{B9}$$

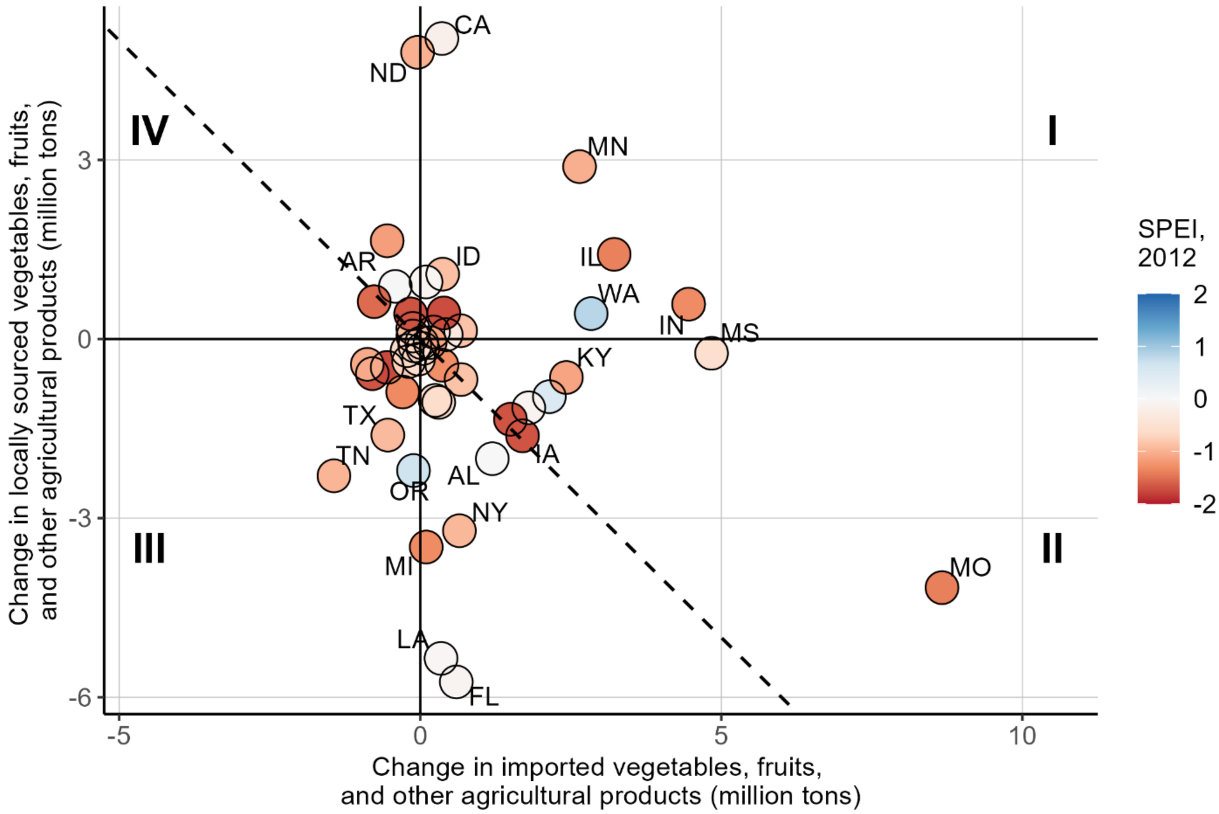
$$\sum_i^n \frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_k^O \quad \forall\, i \neq j. \tag{B10}$$

The outward effect, or the impact of a local drought on all other states of destination, is the same as equation (B7) but with the i and j indices reversed. The aggregate outward effect is the column sum of the derivative matrix (B3) which can be written as:

$$\sum_i^n \frac{\partial \ln Y_i}{\partial \ln D_{jk}} = \frac{\gamma_k}{2} \cdot \alpha_k^O \sum_i^n \frac{I_{jik}}{M_{ik}} \quad \forall\, i \neq j. \tag{B11}$$

Appendix C. Figure for vegetables, fruits, and other agricultural products (03)

Figure C1. Relationship between locally sourced and imported crops other than cereal grains, change over 2007-2012.

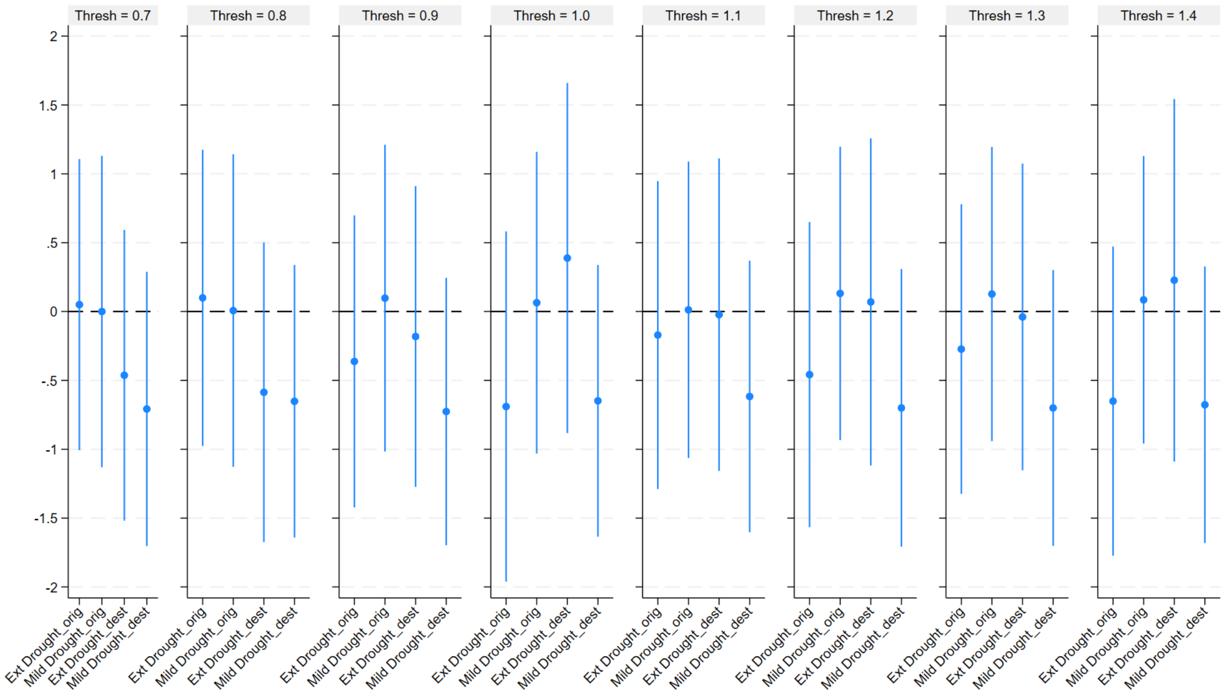


Note: Scatter plot of the change in volume of locally sourced vegetables, fruits, and other agricultural products (y-axis) and imported vegetables, fruits, and other agricultural products (x-axis) from 2007 to 2012 in million tons. The colors of the points represent the SPEI in 2012 where negative (red) values indicate drought and positive (blue) values wetness. States above the y=–x (dashed) line have more available 03 products relative to 2007, and states below it have less products. *Source*: Authors' construction with data from FAF (2023) and ERA5-Land (Muñoz Sabater, 2019).

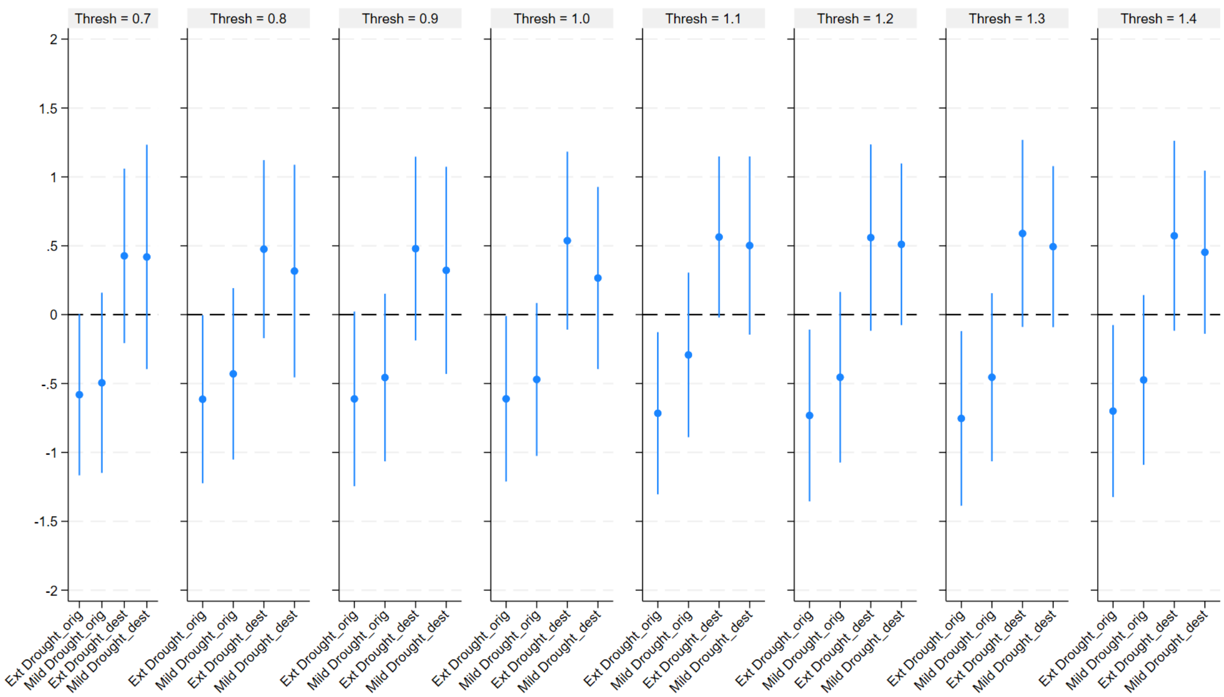
Appendix D. Robustness checks for gravity model estimates

Figure D1: Robustness checks – Gravity model estimates of extreme/mild drought with different thresholds for animals and fish (a), cereal grain (b), and vegetables, fruits and other products (c)

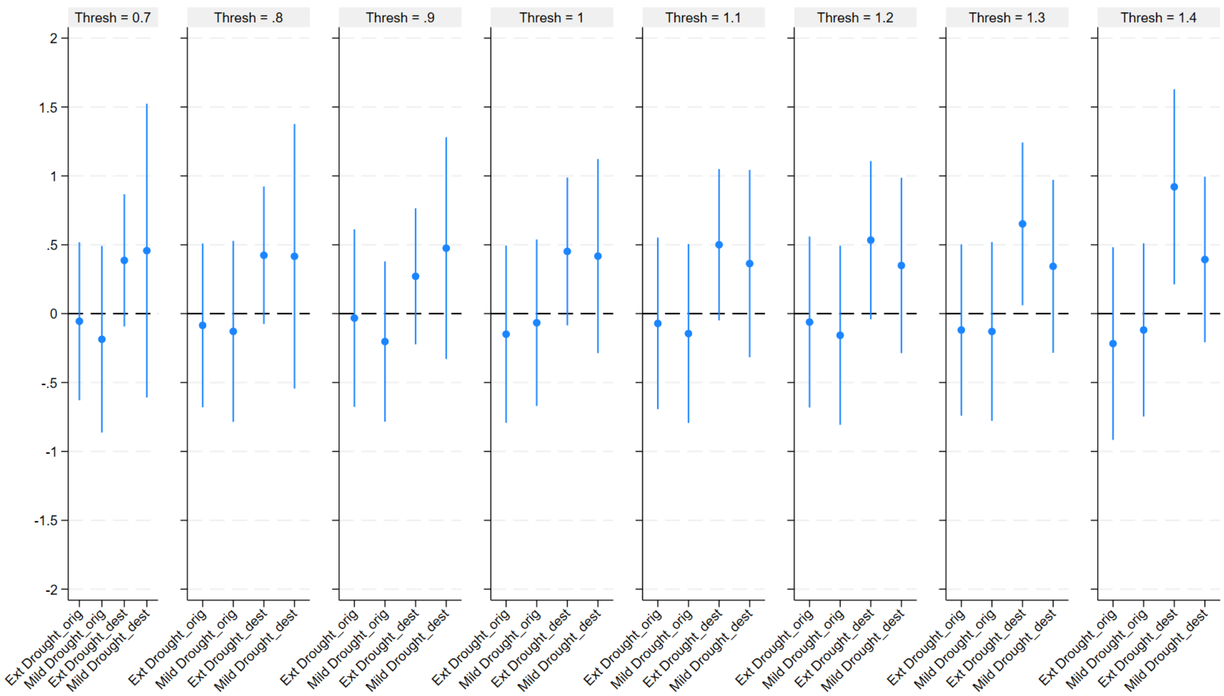
(a)



(b)



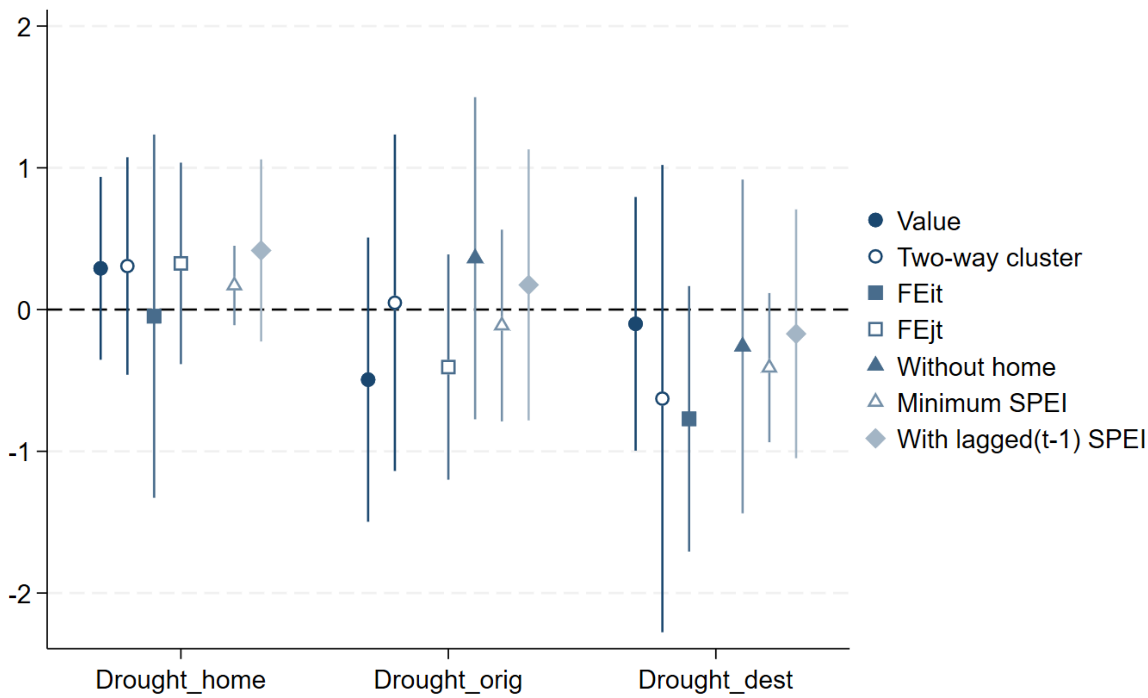
(c)



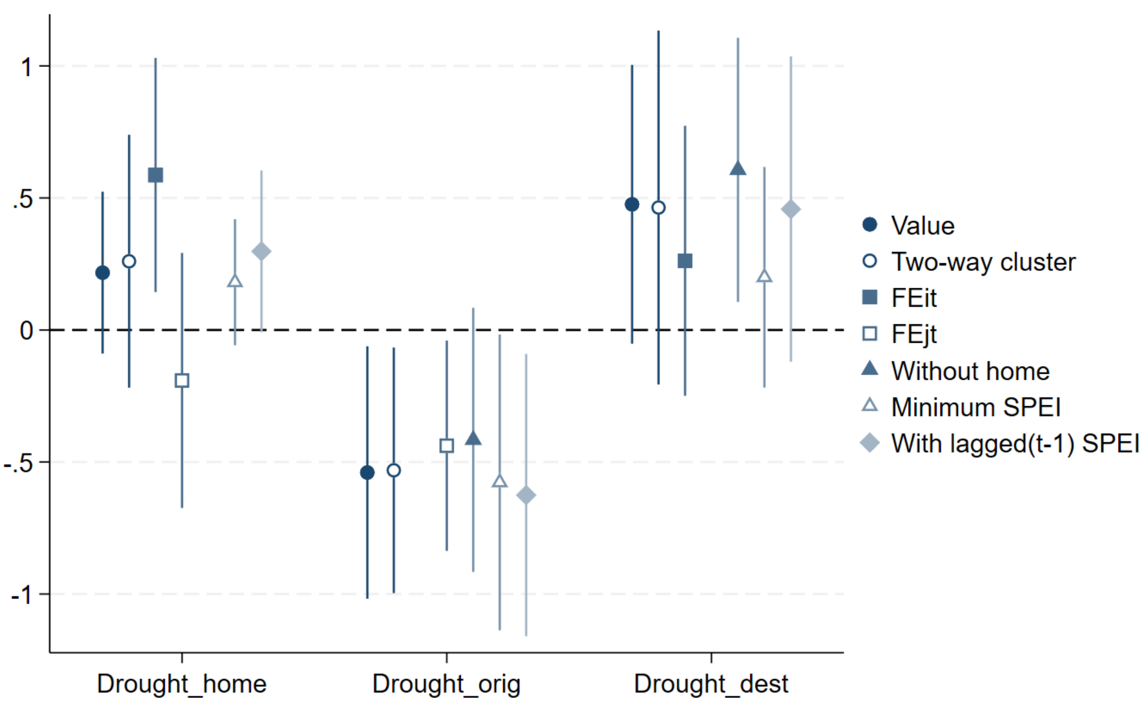
Note: Each panel shows the 95 confidence interval (CI) of the estimates for extreme/mild drought in the importing and exporting states with different thresholds. The specifications remain the same with the same set of covariates and fixed effects as our main empirical specification.

Figure D2: Robustness checks – Gravity model estimates for animals and fish (a), cereal grain (b), and vegetables, fruits and other products (c)

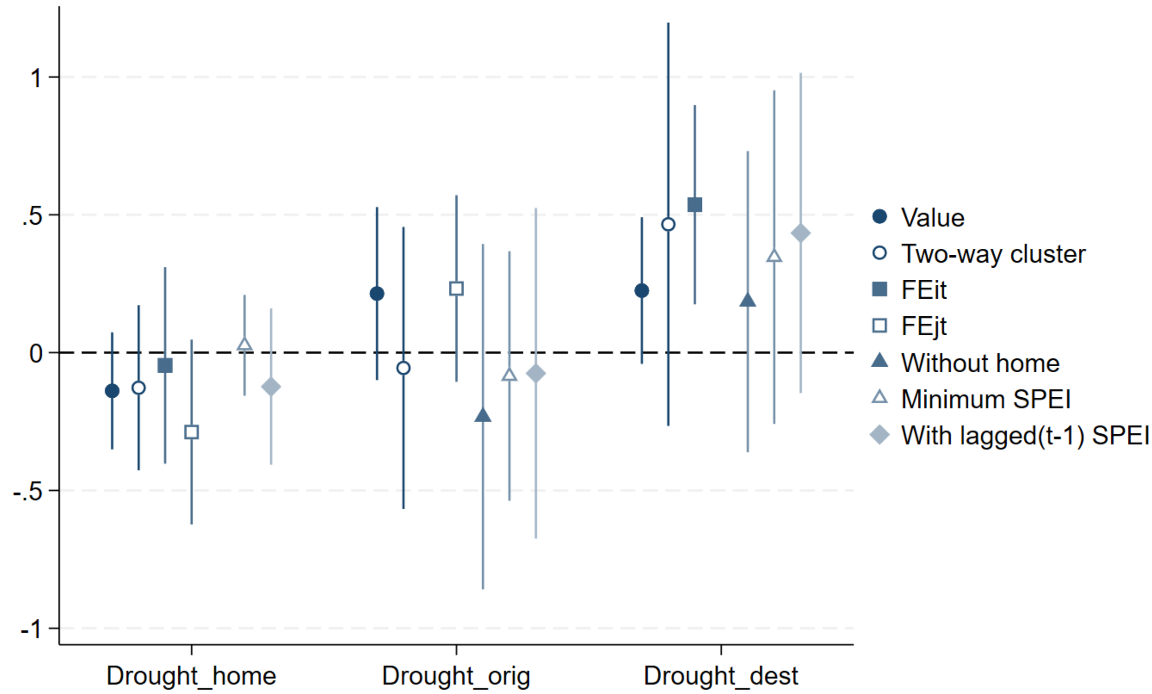
(a)



(b)



(c)



Note: The graph shows the 95% confidence interval (CI) of the estimates for three drought variables across (a) animals and fish, (b) cereal grains, and (c) vegetables, fruits, and other agricultural products. The first line ("Value") of each variable is the CI of the estimate when the dependent variable is measured in monetary values (million U.S.$). The second lines are the estimated coefficients and CIs when standard errors are two-way clustered by exporter and importer. The third lines are the estimates with exporter-importer and exporter-by-year fixed effects ("FEit"). The estimates including importer-by-year fixed effects are presented as "FEjt". Next, are the CIs for respective drought variables without the home-drought variable. The estimates using the minimum monthly SPEIs (as opposed to the average) are also shown. The last vertical lines are the CIs for drought variables for specifications including lagged weather variables.

Appendix E. Robustness checks for manufactured food production function

Table E1. Production function estimates for SCTG04–07

	With drought (1)		With extreme/mild drought (2)	
	Coefficient	Std. Error	Coefficient	Std. Error
Panel A. NLS estimates				
Output elasticities				
Capital	0.265**	(0.111)	0.262**	(0.106)
Labor	0.529***	(0.152)	0.528***	(0.138)
Animals and fish (01)	–0.014	(0.031)	–0.016	(0.025)
Cereal grains (02)	0.066	(0.044)	0.066*	(0.041)
Vegetables, fruits, and other (03)	0.153*	(0.080)	0.160**	(0.071)
Elasticities of substitution				
Animals and fish (01)	0.308	(6.629)	0.222	(3.573)
Cereal grains (02)	0.855	(11.850)	0.838	(8.339)
Vegetables, fruits, and other (03)	1.136	(15.156)	1.150	(8.48)
Marginal effects				
Animals and fish (01)	–0.007	(0.015)	–0.008	(0.013)
Cereal grains (02)	0.033	(0.022)	0.033*	(0.020)
Vegetables, fruits, and other (03)	0.077*	(0.040)	0.080**	(0.035)
Panel B. OLS estimates				
Output elasticities (marginal effects)				
Capital	0.197	(0.133)	0.195	(0.133)
Labor	0.579***	(0.187)	0.577***	(0.188)
Animals and fish (01)	–0.013	(0.013)	–0.013	(0.013)
Cereal grains (02)	0.050*	(0.027)	0.050*	(0.027)
Vegetables, fruits, and other (03)	0.075	(0.049)	0.077	(0.050)
Observations	240	240	240	240

Note: Dependent variable is the value of food manufacturing (04–07) without beverages and tobacco products. Standard errors are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Column 1 shows coefficients that include agricultural input variables estimated from the gravity model with drought. Column 2 shows results when including agricultural input variables estimated with extreme/mild drought. Panel A reports the nonlinear least squares (NLS) estimators with state and year dummies. Each column of Panel A reports the parameter estimates and the marginal effects ($\frac{\gamma}{2}$) of locally grown and imported inputs of each commodity SCTG 01–03. The NLS standard errors are bootstrapped based on 200 replications clustered at the state level. Panel B reports the ordinary least squares (OLS) estimators with state and year fixed effects, and the standard errors are clustered at the state level.

Table E2. Production function estimates with alternative capital measurements

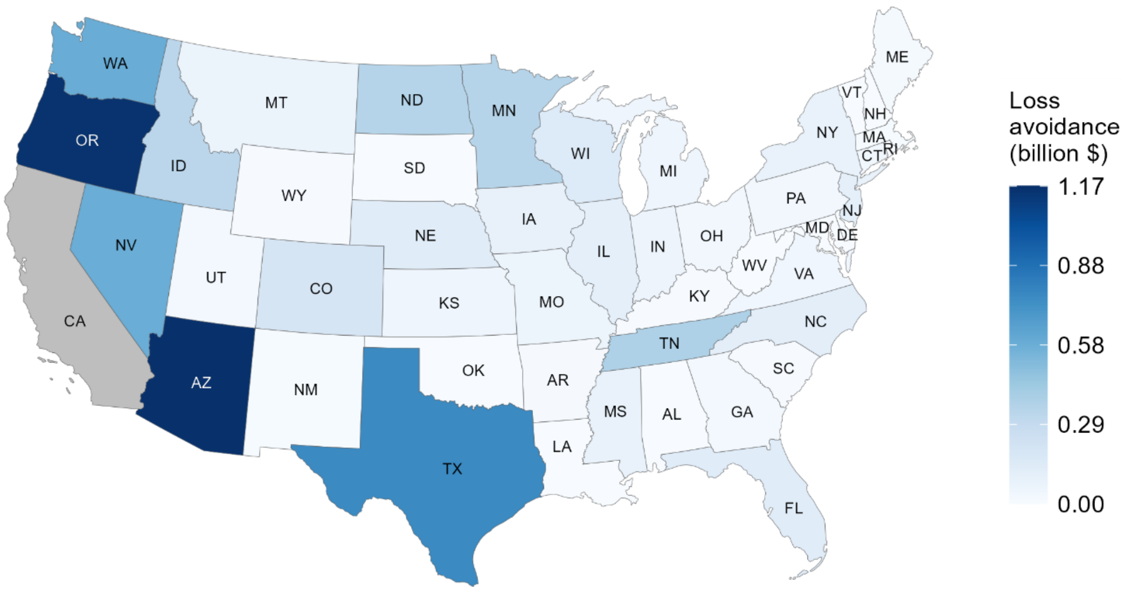
	With drought (1)		With extreme/mild drought (2)	
	Coefficient	Std. Error	Coefficient	Std. Error
Panel A. NLS estimates				
Output elasticities				
Capital	0.200**	(0.091)	0.199**	(0.089)
Labor	0.591***	(0.128)	0.586***	(0.121)
Animals and fish (01)	–0.024	(0.033)	–0.025	(0.033)
Cereal grains (02)	0.105**	(0.047)	0.106**	(0.048)
Vegetables, fruits, and other (03)	0.128	(0.084)	0.133*	(0.083)
Elasticities of substitution				
Animals and fish (01)	0.342	(7.821)	0.319	(7.015)
Cereal grains (02)	0.748	(6.247)	0.745	(6.922)
Vegetables, fruits, and other (03)	1.155	(8.895)	1.160	(11.534)
Marginal effects				
Animals and fish (01)	–0.012	(0.017)	–0.012	(0.016)
Cereal grains (02)	0.053**	(0.024)	0.053**	(0.024)
Vegetables, fruits, and other (03)	0.064	(0.042)	0.067*	(0.041)
Panel B. OLS estimates				
Output elasticities (marginal effects)				
Capital	0.196**	(0.095)	0.195**	(0.095)
Labor	0.594***	(0.144)	0.590***	(0.145)
Animals and fish (01)	–0.005	(0.014)	–0.006	(0.014)
Cereal grains (02)	0.057**	(0.027)	0.057**	(0.027)
Vegetables, fruits, and other (03)	0.054	(0.051)	0.056	(0.053)
Observations	240	240	240	240

Note: Dependent variable is the value of food and beverage manufacturing. Standard errors are reported in parentheses. $p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ *. Column 1 shows coefficients that include agricultural input variables estimated from the gravity model with drought. Column 2 shows results when including agricultural input variables estimated with extreme/mild drought. Panel A reports the nonlinear least squares (NLS) estimators with state and year dummies. Each column of Panel A reports the parameter estimates and the marginal effects ($\frac{\gamma}{2}$) of locally grown and imported inputs of each commodity SCTG 01–03. The NLS standard errors are bootstrapped based on 200 replications clustered at the state level. Panel B reports the ordinary least squares (OLS) estimators with state and year fixed effects, and the standard errors are clustered at the state level.

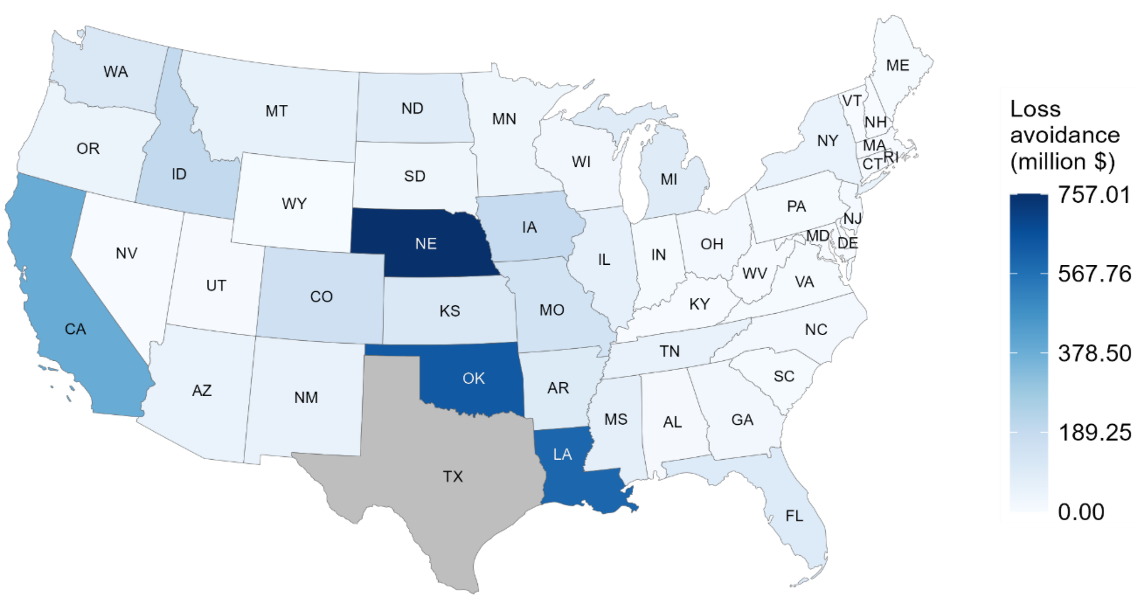
Appendix F. Maps for vegetables, fruits, and other agricultural products (03)

Figure F1. Loss avoidance in the food and beverages manufacturing production of California (a) and Texas (b) following a 100% drought increase in California and Texas (gray) and a shift in the places of import (colored)

(a)



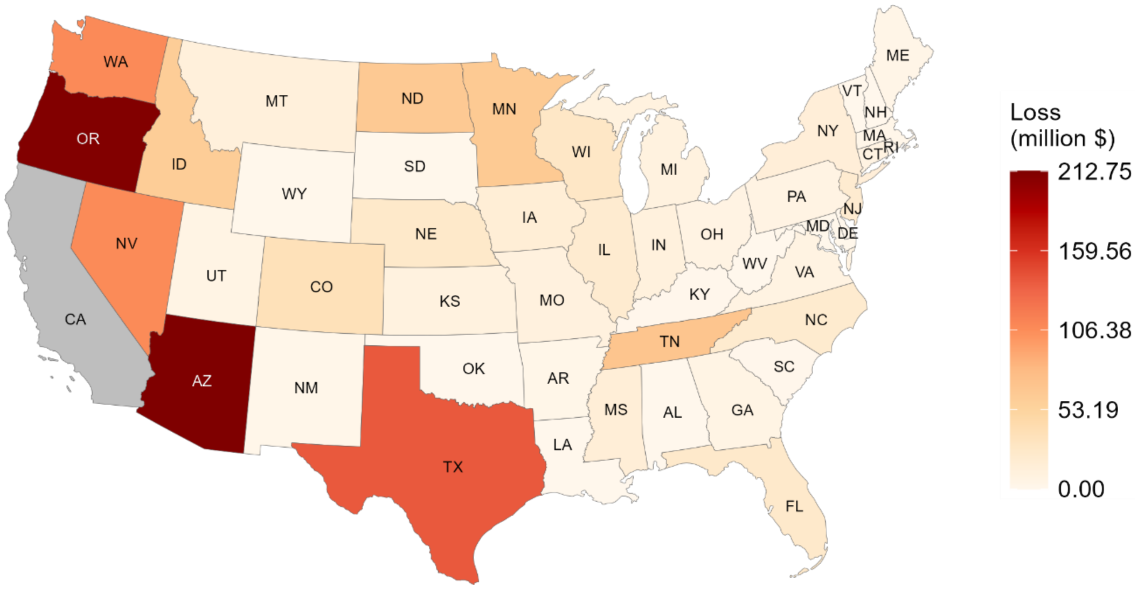
(b)



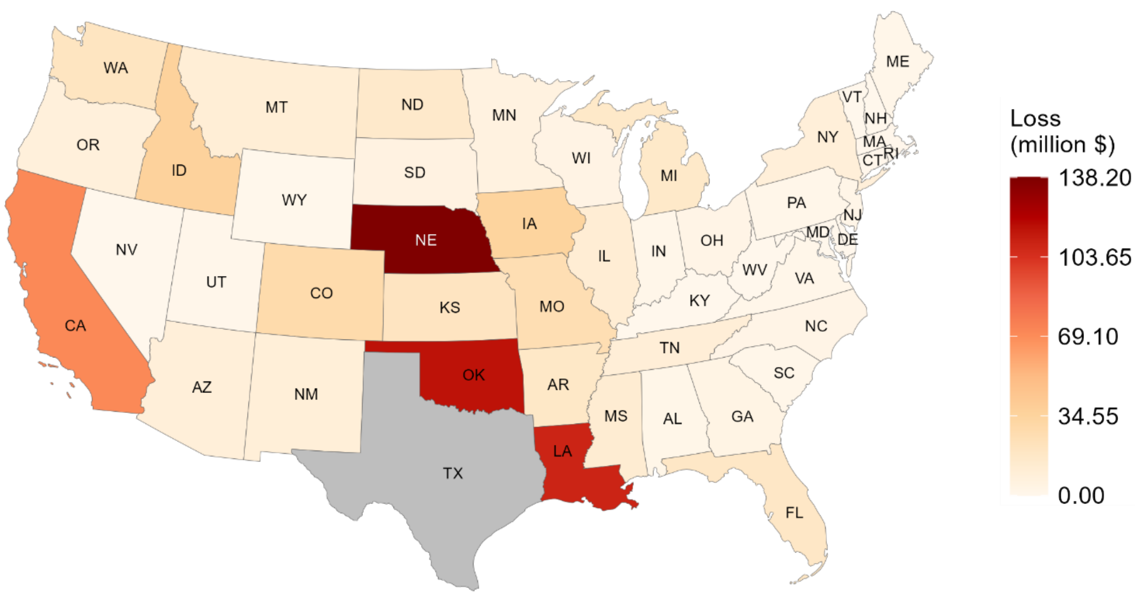
Note: Each impact is estimated as $\frac{\gamma\alpha^D}{2} \cdot \frac{I_{i,CA}}{M_{CA}} \cdot Y_{CA}$ for California. Estimates and standard errors are available upon request.

Figure F2. Loss in the food and beverages manufacturing production of California (a) and Texas (b) following a 100% drought increase in the State of origin (colored)

(a)



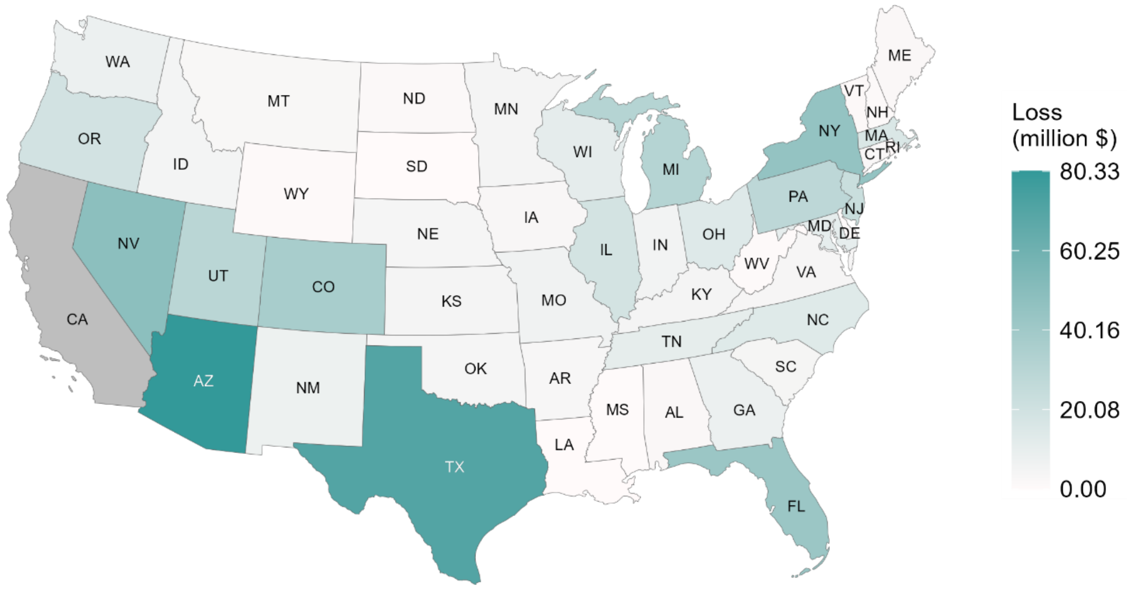
(b)



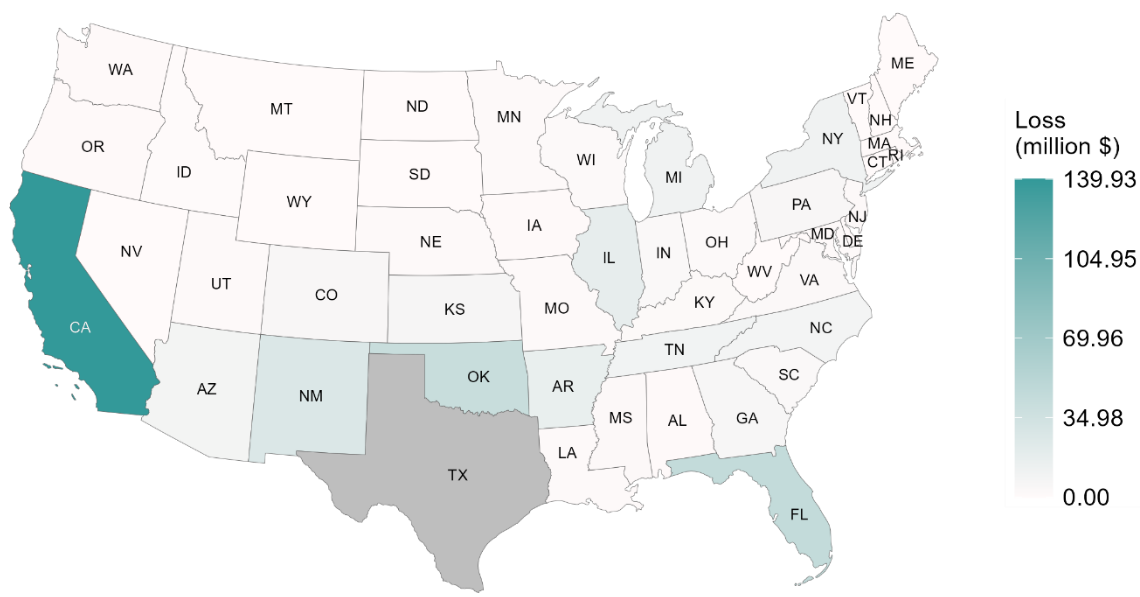
Note: Each impact is calculated as $\frac{\gamma\alpha^{O}}{2} \cdot \frac{I_{i,CA}}{M_{CA}} \cdot Y_{CA}$ for California. Estimates and standard errors are available upon request.

Figure F3. Loss in the food and beverages manufacturing production in the State of destination (colored) following a 100% drought increase in California (a) and Texas (b)

(a)

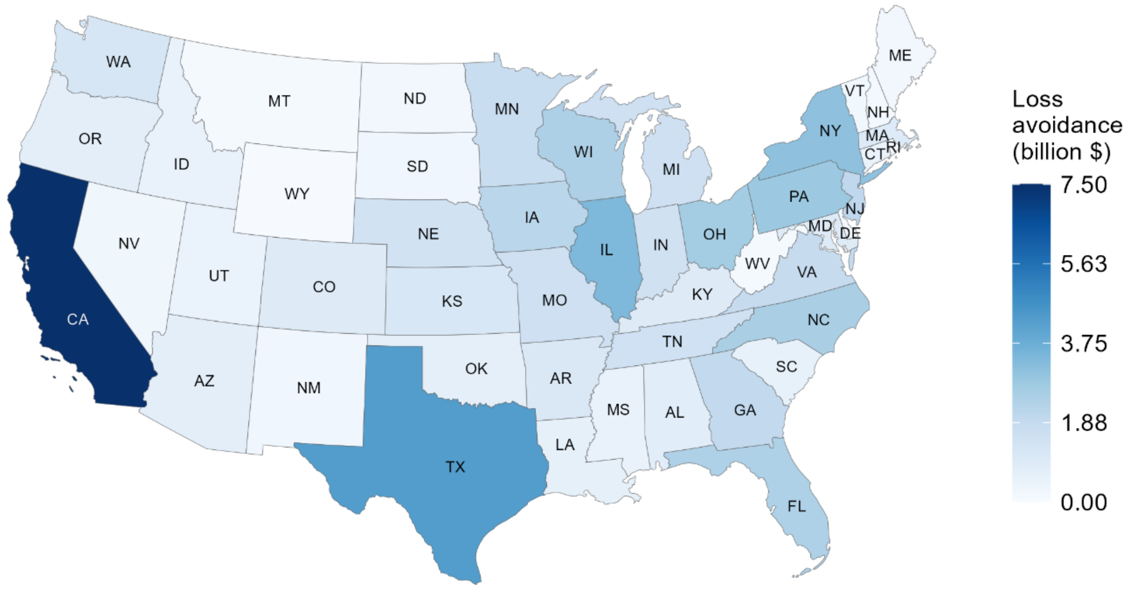


(b)



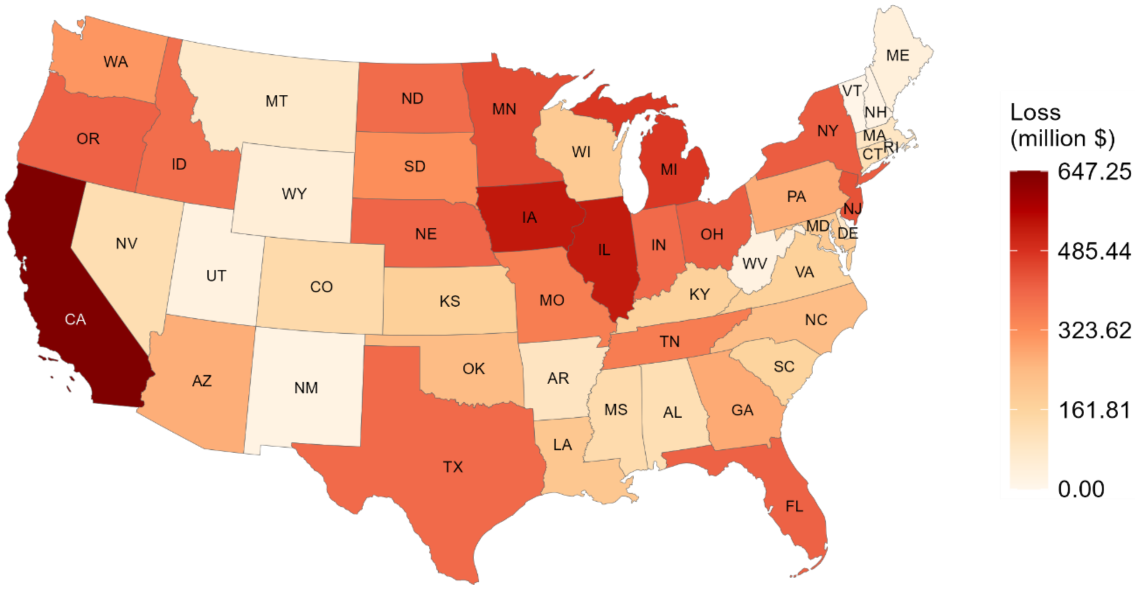
Note: Each impact is calculated as $\frac{\gamma\alpha^O}{2} \cdot \frac{I_{CA,j}}{M_j} \cdot Y_j$ for California. Estimates and standard errors are available upon request.

Figure F4. Sum of avoided losses in the food and beverages manufacturing production of each state (colored)



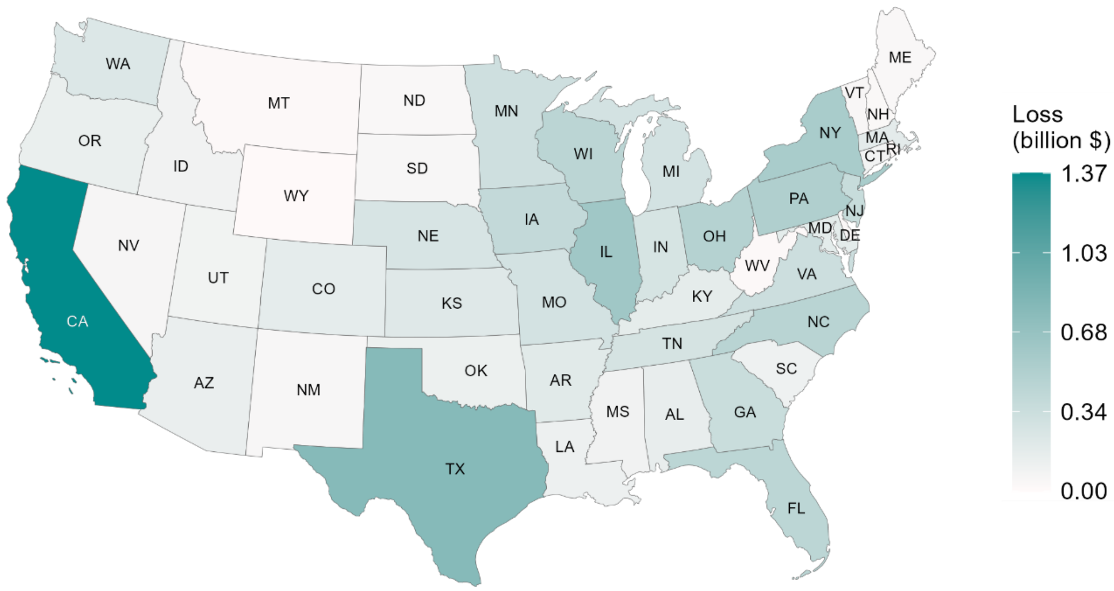
Note: The loss comes from a 100% increase in local drought (colored states) and is avoided by importing vegetables, fruits, and other agricultural products from the rest of the nation. Each impact for state j is calculated as $\frac{\gamma\alpha^D}{2} \cdot Y_j$. Estimates and standard errors are available upon request.

Figure F5. Sum of food and beverage manufacturing production losses in the rest of the nation following a 100% drought increase in the State of origin (colored)



Note: Each impact state j is calculated as $\frac{\gamma\alpha^{O}}{2} \cdot Y_j$. Estimates and standard errors are available upon request.

Figure F6. Food and beverage manufacturing production loss in the State of destination (colored) following a 100% drought increase in the rest of the nation



Note: Each impact state j is calculated as $\frac{\gamma\alpha^{O}}{2}\sum_{i}^{n}(\frac{I_{ji}}{M_i}\cdot Y_i)$. Estimates and standard errors are available upon request.

Appendix G. Estimates for maps

Table G1. Estimates for Figure 5

	Destination			
	California		Texas	
Origin	Coeff.	Std. Err.	Coeff.	Std. Err.
Alabama	0.000	0.000	0.063	0.027
Arizona	7.467	3.165	3.968	1.682
Arkansas	11.259	4.773	19.853	8.416
California			29.745	12.610
Colorado	59.475	25.213	36.860	15.626
Connecticut	0.009	0.004	2.553	1.082
Delaware	0.000	0.000	0.000	0.000
Florida	0.119	0.051	22.683	9.616
Georgia	0.112	0.048	0.026	0.011
Idaho	108.915	46.172	0.953	0.404
Illinois	110.804	46.973	94.530	40.074
Indiana	2.994	1.269	4.281	1.815
Iowa	1,217.482	516.129	38.883	16.484
Kansas	55.962	23.724	1,565.762	663.776
Kentucky	0.705	0.299	0.264	0.112
Louisiana	1.468	0.623	71.429	30.281
Maine	0.000	0.000	0.000	0.000
Maryland	0.000	0.000	0.003	0.001
Massachusetts	0.236	0.100	0.015	0.006
Michigan	4.016	1.703	1.105	0.468
Minnesota	320.691	135.951	68.968	29.238
Mississippi	0.000	0.000	0.306	0.130
Missouri	320.694	135.952	359.340	152.335
Montana	67.497	28.614	0.017	0.007
Nebraska	2,483.890	1053.000	290.238	123.041
Nevada	0.670	0.284	0.000	0.000
New Hampshire	0.000	0.000	0.000	0.000
New Jersey	0.006	0.003	0.000	0.000
New Mexico	0.041	0.017	43.781	18.560
New York	2.663	1.129	0.525	0.222
North Carolina	0.086	0.037	0.014	0.006
North Dakota	251.986	106.825	56.553	23.975
Ohio	22.495	9.536	30.046	12.737
Oklahoma	12.840	5.443	287.593	121.920
Oregon	93.094	39.465	8.695	3.686
Pennsylvania	0.085	0.036	0.331	0.140
Rhode Island	0.000	0.000	0.000	0.000
South Carolina	0.000	0.000	0.000	0.000
South Dakota	128.006	54.266	36.683	15.551
Tennessee	0.194	0.082	0.009	0.004
Texas	128.314	54.396		
Utah	4.231	1.794	0.078	0.033
Vermont	0.000	0.000	0.000	0.000
Virginia	1.106	0.469	0.034	0.014
Washington	0.873	0.370	0.003	0.001
West Virginia	0.000	0.000	0.000	0.000
Wisconsin	0.001	0.000	46.030	19.513
Wyoming	0.005	0.002	0.000	0.000

Note: Coefficients and standard errors are based on parameters estimated in equations (11) and (14). The coefficients are in 2012 million $. The top five states with the highest impacts are highlighted.

Table G2. Estimates for Figure 6

Origin	Destination: California Coeff.	California Std. Err.	Texas Coeff.	Texas Std. Err.
Alabama	0.000	0.000	–0.081	0.034
Arizona	–9.538	4.044	–5.069	2.149
Arkansas	–14.382	6.097	–25.361	10.751
California			–37.997	16.108
Colorado	–75.975	32.208	–47.086	19.961
Connecticut	–0.011	0.005	–3.262	1.383
Delaware	0.000	0.000	0.000	0.000
Florida	–0.153	0.065	–28.976	12.284
Georgia	–0.143	0.061	–0.034	0.014
Idaho	–139.132	58.982	–1.217	0.516
Illinois	–141.545	60.006	–120.756	51.192
Indiana	-3.825	1.622	–5.468	2.318
Iowa	–1,555.256	659.323	–49.670	21.057
Kansas	–71.487	30.306	–2,000.161	847.932
Kentucky	–0.900	0.382	–0.337	0.143
Louisiana	–1.876	0.795	–91.246	38.682
Maine	0.000	0.000	0.000	0.000
Maryland	0.000	0.000	–0.004	0.002
Massachusetts	–0.301	0.128	–0.019	0.008
Michigan	–5.130	2.175	–1.412	0.598
Minnesota	–409.662	173.669	–88.102	37.349
Mississippi	0.000	0.000	–0.390	0.165
Missouri	–409.666	173.670	–459.033	194.599
Montana	–86.223	36.553	–0.022	0.009
Nebraska	–3,173.012	1345.141	–370.760	157.177
Nevada	–0.856	0.363	0.000	0.000
New Hampshire	0.000	0.000	0.000	0.000
New Jersey	–0.008	0.003	0.000	0.000
New Mexico	–0.053	0.022	–55.927	23.709
New York	–3.402	1.442	–0.670	0.284
North Carolina	–0.110	0.047	–0.017	0.007
North Dakota	–321.896	136.462	–72.243	30.626
Ohio	–28.736	12.182	–38.381	16.271
Oklahoma	–16.402	6.953	–367.382	155.745
Oregon	–118.921	50.415	–11.108	4.709
Pennsylvania	–0.108	0.046	–0.422	0.179
Rhode Island	0.000	0.000	0.000	0.000
South Carolina	0.000	0.000	0.000	0.000
South Dakota	–163.519	69.321	–46.860	19.865
Tennessee	–0.248	0.105	–0.012	0.005
Texas	–163.913	69.488		
Utah	–5.405	2.291	–0.099	0.042
Vermont	0.000	0.000	0.000	0.000
Virginia	–1.412	0.599	–0.043	0.018
Washington	–1.116	0.473	–0.004	0.002
West Virginia	0.000	0.000	0.000	0.000
Wisconsin	–0.001	0.000	–58.800	24.927
Wyoming	–0.007	0.003	0.000	0.000

Note: Coefficients and standard errors are based on parameters estimated in equations (11) and (14). The coefficients are in 2012 million $. The top five states with the highest impacts are highlighted.

Table G3. Estimates for Figure 7

	Origin			
	California		Texas	
Destination	Coeff.	Std. Err.	Coeff.	Std. Err.
Alabama	–0.004	0.002	–2.928	1.241
Arizona	–8.270	3.506	–68.968	29.238
Arkansas	–0.085	0.036	–17.825	7.557
California			–163.913	69.488
Colorado	–0.478	0.203	–64.550	27.365
Connecticut	–2.665	1.130	–0.001	0.000
Delaware	0.000	0.000	0.000	0.000
Florida	–6.187	2.623	–6.435	2.728
Georgia	–0.933	0.396	–1.139	0.483
Idaho	–0.988	0.419	–0.265	0.112
Illinois	–0.769	0.326	–14.540	6.164
Indiana	–0.012	0.005	–0.292	0.124
Iowa	–58.545	24.819	–1.410	0.598
Kansas	0.000	0.000	–24.111	10.222
Kentucky	0.000	0.000	–0.156	0.066
Louisiana	–0.008	0.003	–1.666	0.706
Maine	0.000	0.000	0.000	0.000
Maryland	–2.981	1.264	–0.001	0.001
Massachusetts	0.000	0.000	–0.248	0.105
Michigan	–4.824	2.045	–0.065	0.028
Minnesota	–3.206	1.359	–0.139	0.059
Mississippi	–0.202	0.086	–3.576	1.516
Missouri	–4.173	1.769	–9.337	3.958
Montana	–0.060	0.026	–0.683	0.290
Nebraska	–0.012	0.005	–0.620	0.263
Nevada	–167.1452	70.858	–2.806	1.190
New Hampshire	–0.107	0.045	–14.516	6.154
New Jersey	–0.329	0.139	–384.917	163.178
New Mexico	0.000	0.000	–142.973	60.611
New York	–34.661	14.694	–14.570	6.177
North Carolina	–0.004	0.002	–1.176	0.498
North Dakota	0.000	0.000	0.000	0.000
Ohio	0.000	0.000	–0.678	0.287
Oklahoma	–0.003	0.001	–83.383	35.349
Oregon	–2.610	1.106	–0.496	0.210
Pennsylvania	–0.037	0.016	–4.575	1.940
Rhode Island	0.000	0.000	0.000	0.000
South Carolina	–7.077	3.000	–0.001	0.000
South Dakota	0.000	0.000	–0.001	0.000
Tennessee	0.000	0.000	–0.085	0.036
Texas	–37.997	16.108		
Utah	–1.480	0.627	–7.661	3.248
Vermont	0.000	0.000	–0.024	0.010
Virginia	–0.004	0.002	–0.050	0.021
Washington	–0.945	0.401	–1.979	0.839
West Virginia	0.000	0.000	0.000	0.000
Wisconsin	–0.009	0.004	–0.090	0.038
Wyoming	0.000	0.000	0.000	0.000

Note: Coefficients and standard errors are based on parameters estimated in equations (11) and (14). The coefficients are in 2012 million \$. The top five states with the highest impacts are highlighted.

Table G3. Estimates Figure 8–10

State	Figure 8		Figure 9		Figure 10	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Alabama	601.641	255.055	–138.638	58.773	–768.559	325.817
Arizona	555.889	235.659	–17.780	7.537	–710.113	301.040
Arkansas	789.922	334.873	–137.770	58.405	–1,009.076	427.779
California	5,420.492	2297.919	–346.811	147.024	–6,924.334	2935.446
Colorado	668.619	283.449	–540.763	229.247	– 854.118	362.088
Connecticut	341.350	144.709	–146.904	62.277	–436.053	184.857
Delaware	122.872	52.090	–757.117	320.966	–156.962	66.541
Florida	1,744.434	739.521	–92.107	39.047	–2,228.403	944.691
Georgia	1,408.849	597.256	–316.224	134.057	–1,799.716	762.957
Idaho	367.674	155.869	–846.664	358.928	– 469.681	199.113
Illinois	2,471.424	1047.715	–4,719.611	2000.793	–3,157.087	1338.390
Indiana	1,080.381	458.008	–5,516.011	2338.413	–1,380.118	585.076
Iowa	1,569.441	665.336	–3,751.685	1590.459	–2,004.862	849.925
Kansas	845.371	358.380	–4,635.631	1965.192	–1,079.908	457.807
Kentucky	677.938	287.399	–585.153	248.065	–866.023	367.135
Louisiana	475.928	201.761	–289.189	122.596	–607.967	257.737
Maine	152.062	64.464	–33.509	14.205	–194.249	82.348
Maryland	691.337	293.080	–876.795	371.701	–883.139	374.391
Massachusetts	709.672	300.852	–127.345	53.985	–906.560	384.320
Michigan	1,142.440	484.317	–2,032.741	861.744	–1,459.395	618.684
Minnesota	1,276.647	541.212	–3,464.712	1468.802	–1,630.836	691.363
Mississippi	368.063	156.034	–192.068	81.424	– 470.177	199.323
Missouri	1,135.268	481.276	–2,650.007	1123.422	–1,450.233	614.800
Montana	78.055	33.090	–850.961	360.750	–99.710	42.270
Nebraska	1,045.122	443.060	–6,604.415	2799.822	- 1,335.076	565.981
Nevada	225.590	95.635	–1.887	0.800	–288.177	122.168
New Hampshire	119.488	50.655	–19.656	8.333	–152.638	64.708
New Jersey	1,463.075	620.244	–552.452	234.202	–1,868.986	792.323
New Mexico	198.459	84.133	–92.274	39.118	–253.518	107.474
New York	2,245.228	951.824	–1,005.005	426.053	–2,868.136	1215.894
North Carolina	1,827.375	774.682	–407.277	172.658	–2,334.356	989.608
North Dakota	150.500	63.802	–3,348.352	1419.473	–192.254	81.503
Ohio	1,930.688	818.480	–4,635.173	1964.997	–2,466.331	1045.556
Oklahoma	497.905	211.078	–921.847	390.800	–636.042	269.638
Oregon	543.316	230.329	–283.465	120.170	–694.052	294.231
Pennsylvania	2,057.793	872.364	–1,024.241	434.208	–2,628.699	1114.389
Rhode Island	72.051	30.545	–5.055	2.143	–92.041	39.019
South Carolina	439.336	186.248	–193.048	81.839	–561.224	237.921
South Dakota	200.241	84.889	–2,007.447	851.021	–255.796	108.440
Tennessee	1,105.953	468.849	–813.520	344.877	–1,412.784	598.924
Texas	3,122.217	1323.607	–1,042.851	442.098	–3,988.433	1690.824
Utah	359.642	152.464	–34.395	14.581	–459.420	194.763
Vermont	179.276	76.001	–128.546	54.495	–229.014	97.086
Virginia	1,338.452	567.412	–658.828	279.298	–1,709.787	724.833
Washington	900.423	381.718	–384.197	162.873	–1,150.233	487.620
West Virginia	90.206	38.241	–75.016	31.802	–115.233	48.851
Wisconsin	1,774.450	752.246	–2,152.097	912.343	–2,266.747	960.946
Wyoming	26.527	11.246	–82.904	35.145	–33.887	14.366

Note: Coefficients and standard errors are based on parameters estimated in equations (11) and (14). The coefficients are in 2012 million $. The top five states with the highest impacts are highlighted.