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

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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 such as droughts decrease agricultural yield and harvested areas, impact the domestic trade of agricultural products and, in turn, food manufacturing. We investigate this relationship at the state level by estimating the food manufacturing production function in a two-stage instrumental variable estimation process. We first assess how drought affects trade in animals and fish (SCTG 01), cereal grains (SCTG 02), and all other crop products (SCTG 03). Next, we estimate a nested production function for processed food. Our findings indicate that the impact of a drought is far from being confined to the area where it happens. At the national level, we find that a 1% increase in drought in the states producing agricultural commodities reduces their exports to other states by 0.5%–0.7% which, in turn, reduces food manufacturing production by an average of 0.04%. The capacity to shift the origin of import flows, adjust their volume, and substitute agricultural inputs supports the resilience of the food manufacturing sector. We further estimate the 48×48 pairwise dependence across states and by commodity group. While cereal grain production is more spatially concentrated than other crops, the agrifood supply chain can enhance its resilience by sourcing from geographically diverse counties within key supplier states and improving multi-state coordination. These findings provide important insights for policymakers and industry stakeholders willing to reduce the food system vulnerability to extreme weather events.

Keywords: Agrifood supply chain, agricultural trade, extreme weather, climate change

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 this trend will intensify in the decades to come (IPCC, 2022). Extreme weather events such as droughts and extreme moisture reduce agricultural yield (Lesk et al., 2016; Kuwayama et al., 2019; Vogel et al., 2019; Cheng et al., 2022) and harvested areas (Iizumi and Ramankutty, 2015; Raymond et al., 2020; Rathore et al., 2024), alter the domestic trade of agricultural products (Dall'erba et al., 2021; Nava et al., 2023) and, in turn, affect the manufacturing of food products[1] since the former are necessary inputs in the production of the latter (Davis et al., 2021). A recent example is drought-struck Nebraska which in 2012 had to import 2.65 times as many agricultural commodities from other U.S. states than under regular weather conditions 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 (Producer Price Index program staff, 2012) (Fig. 1).

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 food manufacturing

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[1] Food products refer to a wide range of products such as animal feed, meat and its preparation, milled grain products, foodstuffs, beverages, and tobacco products. Throughout the manuscript, we group them under the generic name of manufactured food products.

industry and then to final consumers. Trade adjustments reduce welfare losses in the agricultural sector (Gouel and Laborde, 2021; Nava et al., 2023), partially compensate for losses in yields and profits (Costinot et al., 2016; Ferguson and Gars, 2020; 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 studies that focus on the impact of the Ukraine-Russia war on the global food system (Laber et al., 2023) and on extreme weather events on the Australian food system (Malik et al., 2022). A notable difference with our work is that we do not treat the agrifood trade as fixed. The cascading impact of supply disruption is contingent on the restructuring of import relations after a perturbation has occurred, as advocated in the trade economics literature. To our knowledge, only one other article uses this approach for the global food system (Jagermeyr et al., 2020), but it limits its analysis to maize and wheat, and perturbation emanates from a war rather than a climate shock.

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; Costinot et al., 2016; 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 most of the country's agrifood products are for the domestic market, although 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 less than 20% (Beckman et al., 2017). Similarly, the share of imports for food and beverages consumption from the international market has remained low at approximately 15% (Beckman et al., 2017). In addition, the BTS data used in this manuscript distinguishes the interstate trade flows which have a U.S. destination for 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. [2] Our manuscript focuses on trade flows for the domestic market only.

The domestic focus that this manuscript adopts means that the capacity of adaptation or propagation of risks due to dependence on trade is limited by the range of nationally produced crops, country-wide weather conditions, and the national transportation network (10). 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 (Schmidhuber and Tubiello, 2007; Marchand et al., 2016; Inoue and Todo, 2019; Bertassello et al., 2023). As a result, trade has the short-run potential to mitigate or accentuate the disruptive effects of extreme weather. This challenge highlights the critical need to address the complex impact of extreme weather events on the trade of agricultural commodities and, in turn, on the manufacturing of food, beverages, and livestock feed in the United States.

This study makes several contributions to our understanding of food supply chain resilience in the face of climate shocks. It introduces a two-stage instrumental variable

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[2] According to BTS, the international export share of U.S. agricultural production over 1997–2017 averaged 1.1% for animals and fish, 12.2% for cereal grains, and 13.5% for vegetables, fruits, and other crops. The corresponding import shares were lower: 3.4%, 1.3%, and 9.4%, respectively.

framework that directly links weather-induced disruptions to downstream food manufacturing via domestic trade flows. The paper offers the first quantitative elasticity estimates of drought impacts on both trade and production, and constructs a detailed interstate dependence network by modeling 2,304 (48×48) pairwise trade relationships across agricultural commodity groups. It distinguishes the differential effects of shocks by commodity type and by direction—local, inward, and outward—offering a nuanced picture of vulnerability and shock propagation in the agrifood sector. Through extensive robustness checks and empirical validation, it identifies core resilience mechanisms—substitution, redundancy, and adaptability—and highlights the central role of interstate trade in climate adaptation. Importantly, the study goes beyond national-level analyses by proposing actionable strategies for sub-national actors, including diversified sourcing, infrastructure investment, and governance coordination. Finally, it lays out a scalable framework that can be extended to simulate future climate scenarios and other systemic shocks such as frost, hail, or political conflict, hence providing a valuable foundation for long-term resilience planning. Although a comprehensive analysis of the U.S. domestic food flows has been partially developed in recent years (Smith et al., 2017; Rushforth and Ruddell, 2018; Lin et al., 2019), our study differs in several important ways. First, we adopt a formal gravity model rather than cost-minimization to infer trade flows. The latter approach does not include multilateral resistance terms, a measure of the ease with which states can substitute between trading partners. They are a requirement frequently highlighted in the economics literature (Anderson and van Wincoop, 2003; Head and Mayer, 2014; Yotov et al., 2016). Second, previous contributions focus only on the mass of transported goods, while we test our results to both mass and value as commodity prices fluctuate with several factors such as production costs, supply shocks, and the availability of substitutes. Third, demand shall not be driven by population at destination as many agricultural commodities are not readily edible. Instead, demand originates primarily from the food manufacturing sector and varies by the type of traded commodities. Fourth, and more importantly, we consider the systemwide impact of climatic conditions and extreme weather events at origin and destination places (Dall'erba et al., 2021, 2025). This is particularly critical because the sensitivity of crop yields to weather shocks varies across commodities. Failing to include their presence can lead to biased estimates and suboptimal resilience policies.

Finally, our work responds to long-standing calls for a data- and model-driven approach to identifying and quantifying resilience in food systems (Tendall et al., 2015; Barrett et al., 2020; Gaupp et al., 2020; Fanzo et al., 2021). Resilience, in this context, refers to a system's capacity to maintain, protect, or rapidly restore its key functions despite disruptions. Our findings reveal that the U.S. food system exhibits several resilience attributes outlined by Tendall et al. (Tendall et al., 2015) and Moser et al. (Moser et al., 2019), including robustness (the ability to endure disturbances without compromising food security), redundancy (the presence of backup mechanisms to absorb shocks), and adaptability (the capacity to reconfigure and innovate in response to change). These attributes manifest through shifts in trade flow origins, variations in trade volume, and the substitution of agricultural inputs following extreme weather events—mechanisms that successfully maintain food manufacturing levels over time. Beyond a qualitative assessment, our analysis provides the first quantitative ranking of each destination state's dependence on different origin locations. This demonstrates that resilience can be enhanced by accessing a more extensive and diverse network of suppliers.

2. Data

2.1. Data for the gravity model

The variables used in the estimation of the gravity model and the preprocessing are described in Table D5 (*SI Appendix D*). Data on state-to-state trade flows for animals and fish (SCTG 01), cereal grains (SCTG 02), and other agricultural products (SCTG 03) come from the Freight Analysis Framework (FAF) (*Freight Analysis Framework, FAF5*, 2017). While the Commodity Flow Survey (CFS) is also widely used, we rely on the FAF due to its broader industry coverage—especially for agricultural industries (see *SI Appendix A1* for details). We compile a dataset based on the quinquennial U.S. domestic trade flows from the FAF for the five years between 1997 and 2017. To focus on the domestic market, we exclude all flows that cross state boundaries to enter or leave the country (e.g., sales of Illinois corn to California to ship it to Asia). This approach allows us to retain only domestic freight movements related to domestic agrifood production and consumption. All modes of transportation are considered (e.g., truck, rail, water, and multiple modes). The final dataset covers 34,560 data points (48 states × 48 states × 5 years × 3 commodities). Intrastate flows are also included, both to reflect the decision-making of destination states choosing between local and imported inputs and to reduce bias in state-level effects, as variations in intrastate flows may reflect differences in trade costs or market size (Yotov, 2022). All monetary values are adjusted to 2012 U.S. dollars using the producer price index (*Freight Analysis Framework, FAF5*, 2017).

The exporting state's production capacity is measured as the total value of agricultural exports—both interstate and intrastate—using trade flow data from the FAF. Import-side demand is proxied by the one-year lagged value added of the processed food sector, weighted by the share of each agricultural SCTG 01–03 input sold to food manufacturing, as reported in Table D1 (*SI Appendix D*). Lagged values are used to avoid concurrent effects with production output in the second stage. Food production is measured as value added of the food and beverages manufacturing sector (including tobacco), as classified under NAICS 312 (North American Industry Classification System) by the Bureau of Economic Analysis (BEA) which reports value-added for every five years over 1996–2011 (*Regional Data GDP and Personal Income*, 2023). For 1996, we use SIC-to-NAICS concordance and follow the same procedure used for labor construction (as detailed in *SI Appendix A3*). All monetary values are deflated to 2012 U.S. dollars using the implicit price deflator (*Implicit Price Deflators for Gross Domestic Product*, 2023). Finally, to capture final household demand—given that 5.6–26.2% of SCTG 01–03 are consumed directly (Table D1 in *SI Appendix D*)—we include state population size as a control variable (*Population and Housing Unit Estimates Tables*, 2023).

Drought (wetness) is measured as the absolute values of the negative (positive) measures of the Standardized Precipitation Evapotranspiration Index (SPEI). The 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. For weather controls, we use the growing degree days (GDD) and precipitation. Details on how extreme and normal weather conditions are aggregated using both spatial and temporal weights of each agricultural commodity are provided in *SI Appendix A2*.

Because we approximate the multilateral resistance terms (MRTs) of three bilateral variables in our gravity model—distance, contiguity, and within-state dummy variable—we collect distances between states based on the shortest truck travel time between the most populated cities in the origin and destination states. Travel time is calculated by Open Source Routing Machine. 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 (Mayer and Head, 2002). It 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 shipments by trucks prevail, and out-of-state farm-based agricultural shipments are assumed to be moved by trucks in the FAF (Hwang et al., 2021). Yet, we find that the major shipment mode differs by commodity. For instance, in 2016, 72% of corn, 51% of soybeans, but only 29% of wheat were transported by trucks (Millard, 2019).

2.2. Data used in the food manufacturing production function

The variables used are summarized in Table D6 (*SI Appendix D*). Our sample is composed of observations for the 48 U.S. states in five-year intervals from 1997 and 2017. The time period is constrained by the availability of the FAF trade flow data which we use to construct food production. We follow three steps. First, we exclude all internationally traded flows to focus on domestic trade activity. Production is measured as the sum of intrastate and interstate trade flows, which capture all domestic uses whether for intermediate consumption, final consumption, or inventory. We do this process for each of the SCTG food commodities: animal feed (04), meat/poultry preparations (05), milled grains and bakery products (06), other prepared foods (07), alcoholic beverages (08), and tobacco products (09). We then aggregate these into a single measure of food manufacturing (SCTG 04–09) output by state and year.[3]

Second, for the data on labor, we use total full-time and part-time employment in two NAICS-classified industries: food manufacturing (NAICS 311), and beverage and tobacco product manufacturing (NAICS 312). While the BEA provides annual observations for all 50 states from 1998 onward, data for some states are undisclosed, and values for 1997 are missing. We address both issues by recovering the data (as in *SI Appendix A2*).

Third, since capital stock data are not available at the state-sector level, we construct these values. We allocate capital stocks proportionally to each state's value-added for the food and beverage industry (NAICS 311 and 312) following previous studies (Garofalo and Yamarik, 2002; Peri, 2012; Yamarik, 2013; Maestas et al., 2023). National capital stock figures (in 2012 U.S. dollars) are obtained from the Federal Reserve Board (*FRB Estimates of Manufacturing Investment, Capital Stock, and Capital Services*, 2023). We assume uniform capital-output (capital-labor) ratios in the food manufacturing industry across states, consistent with the high mobility of capital and the tendency for interstate adjustments in the capital-labor ratio so that capital returns are equal across states (Peri, 2012).

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[3] The BEA data on manufactured food and beverage production cannot be used as the dependent variable in 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.

Intermediate crop and livestock inputs—both locally produced and imported—are measured as the sum of trade inflows from the FAF data for each SCTG: animals and fish (01), cereal grains (02), and vegetables, fruits, and other crops (03). Local inputs refer to intrastate flows where the origin and destination are the same, while imported inputs capture total inflows from all other states.

3. Empirical method

3.1. Gravity-based instrumental variables (IV) approach

To this end, we estimate a separate gravity model for each of the agricultural input categories (SCTG 01–03). We then use the predicted bilateral trade flows to construct instruments (Eq. 4). Finally, we estimate a second-stage production function of manufactured food output (Eq. 3) using two-stage least squares (2SLS). In the first stage, observed agricultural input flows are regressed on the gravity-based instruments; in the second stage, the output elasticities are estimated based on the instrumented agricultural inputs. This approach allows us to isolate the causal effect of input availability on food manufacturing, leveraging variation in input trade.

3.2. Production function of food manufacturing

We specify a system of structural equations for manufactured food production, alongside equations for endogenous agricultural inputs.

First, we begin by modeling the production function, incorporating inputs sourced either locally or from other regions, as shown in Eqs. 1 and 2. The final output of food manufacturing follows a Cobb-Douglas (CD) production function, comprising aggregate labor, capital, and a composite of primary inputs, assuming constant returns to scale. The CD form implies a unitary elasticity of substitution among capital, labor, and the agricultural input aggregate, meaning that changes in their relative price will not vary the ratio of these inputs. Within each input aggregate, agricultural commodities are assumed to be sourced from two origins—local and out-of-state—with constant elasticity of substitution (CES) (Baier and Bergstrand, 2009; Anderson and Yotov, 2016).

$$Y_{jt} = PT_j L_{jt}^{(1-\beta-\sum_k \gamma_k)} {K_{jt}}^{\beta} \prod_{k=1}^{3} I_{jkt}^{\gamma_k}, \qquad [1]$$

$$I_{jkt} = \left[(I_{hkt})^{\frac{\sigma_k - 1}{\sigma_k}} + \left(M_{jkt}\right)^{\frac{\sigma_k - 1}{\sigma_k}} \right]^{\frac{\sigma_k}{\sigma_k - 1}}, \qquad [2]$$

where Y_{jt} is the production of food manufacturing of state j in year t, and PT_j is sectoral technological productivity. Aggregate labor and capital are L_{jt} and K_{jt} respectively. I_{jkt} is the agricultural input sub-aggregate for each crop and livestock commodity k. I_{hkt} denotes inputs from the home state, and $M_{jkt} = \sum_i^{47} I_{ikt}$ represents imports from all other states i. The inputs are animals and fish ($k = 1$), cereal grains ($k = 2$), and the remaining crops ($k = 3$). These inputs are endogenous to food production and thus they need to be instrumented.

We estimate the log form of Eqs. 1 and 2:

$$\ln Y_{jt} = \left(1-\beta-\sum_{k=1}^{3}\gamma_k\right)\ln L_{jt} + \beta\ln K_{jt} + \sum_{k=1}^{3}\gamma_k \ln\left[(I_{hkt})^{\frac{\sigma_k-1}{\sigma_k}} + \left(M_{jkt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}} \qquad [3]$$

$$+ \mu_j + \nu_t + \varepsilon_{jt},$$

where the coefficients β and γ_k capture output elasticities, while σ_k denotes substitution elasticity between local and imported commodities, as both enter the manufactured food production process. We do not estimate σ_k directly. Instead, we use a baseline elasticity value of 1. To assess robustness to the presence of substitution, we re-estimate the equation using three alternative elasticity values—1.2, 1.5, and 2—which reflect increasing substitution capability. As outlined in *SI Appendix G*, all the results remain consistent. Finally, in Eq. 3, the two-way fixed effects are captured by μ_j and ν_t while ε_{jt} is the error term clustered at the state level.

The estimation of Eq. 3 is implemented by 2SLS. We instrument agricultural inputs with constructed instruments—predicted flows from a structural gravity model of trade. The identifying assumption is that exogenous variation—principally due to local and distant weather shocks—affects food manufacturing output in importing states only through its impact on input availability and trade. This parallels the approach employed in studies of international trade and growth, such as Frankel and Romer (Frankel and Romer, 1999) and Felbermayr and Gröschl (Felbermayr and Gröschl, 2013), where geography-based or weather-induced trade variation is used as an instrument for openness.

3.3. Construction of instruments

Following previous applications in the trade-growth literature (Frankel and Romer, 1999;

Felbermayr and Gröschl, 2013; Feyrer, 2019; Dorn et al., 2022), we construct k instruments. Specifically, we generate a CES aggregate of agricultural inputs sourced locally and imported from other states. The constructed instrument of each agricultural input sub-aggregate, I_{jkt} in Eq. 2, takes the form:

$$\mathcal{J}_{jkt} = \left[\left(\hat{I}_{hkt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + \left(\widehat{M}_{jkt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}}, \qquad [4]$$

where $\mathcal{J}_{jkt}$ is the gravity-based instrument aggregated with predicted local inputs $\hat{I}_{ijkt}$ and imported inputs $\widehat{M}_{jkt} = \sum_{i=1}^{47} \hat{I}_{ikt}$ from Eq. 5.

3.4. Gravity model of agriculture trade

SI Appendix B specifies an estimable equation of the structural gravity model (Anderson and van Wincoop, 2003; Anderson and Yotov, 2016). We estimate the equation by the Poisson Pseudo-Maximum Likelihood (PPML)[4] following Santos Silva and Tenreyro (Santos Silva and Tenreyro, 2006, 2011), for each commodity: animals and fish ($k = 1$), cereal grains ($k = 2$), and other agricultural goods ($k = 3$). In addition, since our analysis centers on the role of locally produced agricultural inputs in food manufacturing, we include within-state weather conditions as denoted with subscript h:

$$I_{ijt} = \exp\{a + \alpha_1 \ln D_{ht} + \alpha_2 \ln D_{it} + \alpha_3 \ln D_{jt} + \delta_1 \ln W_{ht} + \delta_2 \ln W_{it} + \delta_3 \ln W_{jt} \qquad [5]$$

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[4] The PPML estimator is preferred over ordinary least squares (OLS) for estimating the gravity model. OLS drops zero trade flows—i.e., 25%, 20%, and 25% of observations in SCTG 01, 02, and 03, respectively—and produces biased estimates under heteroskedasticity, which is common in trade data.

$$+Z_{ht}'\lambda_1 + Z_{it}'\lambda_2 + Z_{jt}'\lambda_3 + MRT_{ijt}'\phi + \zeta_{ij} + \eta_{CZ_it} + \theta_{CZ_jt}\} + \epsilon_{ijt}.$$

Outcome I_{ijt} is the volume of traded crops and livestock from origin state i to destination state j in year t. Drought (at home D_{ht}, origin D_{it}, and destination D_{jt}) and wetness (at home W_{ht}, origin W_{it}, and destination W_{jt}) are the two (growing season) weather variables of which extreme values traditionally affect crop and livestock production (Lesk et al., 2016; Escarcha et al., 2018; Ray et al., 2018). Z_{ht} is a vector of within-state weather variables (e.g., GDD and precipitation). For the origin and destination locations, Z_{it} and Z_{jt} capture the growing season weather and the economic variables (e.g., agricultural and manufactured food production). Finally, MRT includes the approximated MRTs following Baier and Bergstrand (Baier and Bergstrand, 2009) (as detailed in *SI Appendix B*).

Our focus is on the estimated effects of extreme weather. The coefficient α_1 captures the home-effect of drought—its impact on locally traded commodities consumed within the same state. The estimates on exports (α_2) and imports (α_3) measure the effect of drought on all interstate trade ($i \neq j$). Similarly, $\delta_1, \delta_2,$ and δ_3 capture the effects of wet conditions within, from, and to the state. Pairwise fixed effects ζ_{ij} control 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. Climate-zone-by-year fixed effects—η_{CZ_it} and θ_{CZ_jt}—absorb variation in climate, soil, and irrigation across zones. The error term ϵ_{ijt} is clustered by state-pair.

We also estimate an alternative specification that distinguishes between extreme and mild drought. We define extreme dry conditions when the SPEI is above or equal to the threshold of 1.3[5] in absolute value. Mild drought is defined as SPEIs below 1.3 in absolute term.

While our main specification uses the full structural gravity model to construct instruments—capturing how trade flows respond to the productive capacity of both exporting and importing states—we also report results using a more restrictive, strictly exogenous version. Here, instruments are constructed from characteristics of the exporting states and exogenous weather shocks, bilateral and climate-zone-by-year fixed effects, following a standard approach in the literature (Frankel and Romer, 1999; Felbermayr and Gröschl, 2013). For our maps and matrices, we rely on the full gravity model to preserve its structural interpretation: trade flows are jointly shaped by production and demand fundamentals across states. This allows us to remain consistent with the structural microeconomic foundations of the gravity model, to capture the bilateral nature of agricultural trade more realistically, and to avoid a missing variable bias.

3.5. Validity of the IV approach and robustness checks

This empirical application allows us to estimate the impact of weather shocks in i on the production of manufactured food in j as it occurs exclusively through trade of inputs. The validity of this approach depends on the strength of the gravity-based instruments. The Cragg–Donald F-statistic (or the Kleibergen-Paap Wald F-statistic that is robust to

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[5] The threshold is from the U.S. Drought Monitor Drought Classification (National Drought Mitigation Center, n.d.).

heteroskedasticity) for weak instruments—commonly used in models with a single endogenous regressor—is not applicable in our setting, which involves multiple endogenous variables. Instead, we assess for weak instruments using the Sanderson–Windmeijer (SW) conditional *F*-statistics that evaluate each endogenous regressor conditional on the others (Sanderson and Windmeijer, 2016). Table D3 (in *SI Appendix D*) reports both the SW *F*-statistics and the reduced-form *F*-statistics in order to test the joint significance of the excluded instruments. Because critical values for the SW test are not available when the number of endogenous regressors exceeds two (Stock and Yogo, 2002; Sanderson and Windmeijer, 2016), we follow the convention: an F-statistic below 10 suggests weak instruments (Staiger and Stock, 1997). Our findings indicate that all reported statistics exceed this threshold.

Furthermore, the gravity-based instruments must be uncorrelated with the error term in Eq. 3 to satisfy the exclusion restriction. This condition would be violated if the variables used to construct the instruments affect food output through channels other than the endogenous regressor. While variables such as weather, exporters' agricultural production, and bilateral trade frictions are exogenous with regards to the importing state j's food output (Felbermayr and Gröschl, 2013; Feyrer, 2019), the concern still remains with j's determinants as defined by the gravity model—such as lagged food production and population in j—as they could be correlated with food output in j. As such, we use a reduced-form estimation to test whether food output is systematically related to the gravity instrument covariates, controlling for state and year fixed effects. As shown in Table D7, we find no significant relationship. This supports the validity of the instrument based on these covariates. As an additional robustness check, we include importer-level food production and population as controls in the second stage; yet, the main estimates remain unchanged (see Tables F4 and F6 for first-stage results, and Tables F5 and F7 for second-stage results in *SI Appendix F*).

3.6. Effect of drought on food manufacturing

Next, we disaggregate the drought-effects that come from different geographic locations (as in *SI Appendix C*). Once disaggregated, the average drought-effect will include three elements: 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). These effects are captured in the origin-destination matrices of Eq. 6.

$$\frac{\boldsymbol{\partial \ln Y}}{\boldsymbol{\partial \ln D_k}} = \begin{bmatrix} \frac{\partial \ln Y_1}{\partial \ln D_{1k}} & \cdots & \frac{\partial \ln Y_1}{\partial \ln D_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \ln Y_n}{\partial \ln D_{1k}} & \cdots & \frac{\partial \ln Y_n}{\partial \ln D_{nk}} \end{bmatrix}. \qquad [6]$$

4. Results

4.1. Drought and agricultural trade

We provide a nationwide analysis of the impact of extreme weather events in livestock- and commodity-producing areas on the agricultural trade network and, in turn, on the states manufacturing food, beverages and livestock feeds. We use the Freight Analysis Framework (FAF) data on state-to-state domestic trade flows in the United States for every five years between 1997–2017, when such data are collected. More recent data are not available yet. The trade flows are provided for 42 industries as grouped by the

Standard Classification of Transported Goods (SCTG). Our focus is on the trade flows for three agricultural commodities: animals and fish (01), cereal grains (02), and other crops including vegetables, fruits, and soybeans (03). For manufactured agrifood, SCTG groups include animals feed (04), meat preparations (05), milled grains and bakery products (06), other prepared foods and beverages (07), alcoholic beverages (08), and tobacco products (09). A significant share of agricultural products is used as input in food manufacturing: 76.7% of animals and fish, 57.9% of cereal grains, and 33.7% of other crops are used as inputs in the production of manufactured food. A smaller share is sold directly to households. (*SI Appendix D,* Table D1).

When it comes to detecting drought events, we rely on the Standardized Precipitation Evapotranspiration Index (SPEI) as it captures anomalies relative to the historical climate patterns of each specific location. Fig. 1B illustrates the severity of the 2012 drought that struck most of the Midwest, and thus the largest cereal grain (SCTG 02) producing states. Traditionally, Iowa, Illinois, and Nebraska represent as much as 34% of all the production of grains traded within the United States, but in 2012 the production of grains consumed domestically dropped by 16% (in terms of volume, calculated with domestic trade data only) (*Freight Analysis Framework, FAF5,* 2017). For SCTG 01 (Fig. 1A) and 03 (Fig. 1C), the main producers experienced less severe drought, with the exception of soybean producers in Illinois and Iowa (Fig. 1C) that traditionally supply 33% of national output (1997–2007 average volume, according to the United States Department of Agriculture's National Agricultural Statistics Service, USDA NASS) (*Soybeans - Production*, 2023). National average SPEI trends are shown in Fig. D1A (*SI Appendix D*).

In spite of the 2012 drought event that affected many crop producers, the total value of manufactured food production in the United States remained relatively unchanged from 2007, holding steady at around $1.5 trillion (*SI Appendix D,* Fig. D1B). The volume of food produced for domestic use rose steadily by about 6% annually from 1997 to 2012. As such, the stability in total value is not a reflection of higher prices driven by reduced supply—in fact, supply increased.

Fig. 2A shows state-level production of manufactured food and beverages. Leading producers include California ($173 billion on average for 1997–2017), followed by Texas ($100 billion), Illinois ($79 billion), and New York ($72 billion). Together, they account for 30% of national production, as we would expect from states with large populations. However, states differ in how their food production responds to extreme weather events. As shown in Fig. 2B, between 2007 and 2012, California saw a slight decline in food production despite minimal drought exposure. In contrast, Texas and Illinois, maintained production levels comparable to those in 2007 despite more severe weather conditions. This variation highlights how the effects of local extreme weather conditions depend on the states' ability to purchase from alternative producers, the capacity of producers to adapt to extreme conditions, and the availability of crop reserves from previous years.

Fig. 3 displays how states source agricultural inputs locally or from other states. There is a wide dispersion of states that experienced drought ($\text{SPEI} < -1$, colored in red) and therefore had less cereal grain (SCTG 02) products locally available. States in plane 2 (e.g., Iowa, Illinois, Indiana, and Kansas) experienced local production losses but offset them through increased imports. In contrast, states in plane 3 (e.g., Missouri and Ohio) were indirectly affected—experiencing both local production declines and fewer imports, resulting in a net drop in grain availability (as indicated by their positions below the dashed line). Furthermore, we note that while California and Texas were moderately or minimally affected by drought, the states they import grains from were clearly affected by severe drought. Texas (standing on the dashed line) maintained its SCTG 02 levels by adjusting its sources. Specifically, the top states exporting to Texas were Kansas, Nebraska, Missouri, and Illinois in 2007. By 2012, grains from these states decreased by 82%, 83%, and 90%, respectively. Instead, Texas increased imports from Kansas (by 207%), Oklahoma (+41%), and Louisiana (+15%). A similar wide dispersion in sourcing patterns holds for vegetables, fruits, and other crops (SCTG 03) as shown in Fig. D2 in *SI Appendix D*.

In short, being hit by a drought obliges a state to rely more heavily on imports of agricultural commodities, especially when these are grains, fruits, and vegetables. Imports will come from states that have experienced relatively less drought even if they 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. Yet, the ability to source imports from new locations will depend on various factors and thus differs for each state. Given this complexity and limited prior work, a systematic empirical analysis is warranted.

We begin by presenting the estimated coefficients from regressions of the gravity equation (Eq. 5 in *Materials and Methods*). Table D2 (*SI Appendix D*) summarizes the results for each agricultural SCTG. Columns 1 report the estimators of the gravity equation with drought defined by the SPEI. On average, the export of cereal grains

(SCTG 02) increases by 0.46% after a 1% increase in drought in the destination state. However, if the drought takes place in the origin state, then exports decrease by 0.53%. For vegetables, fruits, and other agricultural products (SCTG 03), the estimates have similar directions but are not statistically significant at the 10% level. These findings align with expectations: a local drought reduces productivity, resulting in a lower export volume while simultaneously leading a state to increase its imports. We did not expect a larger elasticity as drought-struck states can rely on storage from the previous year. In addition, we hypothesize that, in the event of a drought, states serve the needs of their local market before they export to other states. Furthermore, results show no consistent relationship for animals and fish (SCTG 01), which we attribute to the broad range of species included in this category, and the prevalence of indoor livestock systems where fans, misters, and air conditioners are available (Schimmelpfennig et al., 1996). Fig. E1 (*SI Appendix E*) confirms that drought impacts on trade remain consistent across various specifications of the gravity model: i) using value—instead of volume—as the dependent variable, ii) two-way clustered standard errors, iii) alternative fixed effects and extreme weather measures, and iv) including lagged SPEIs.

We also control for climate-zone-by-year fixed effects to absorb the elements that are common across states within the same climate zone and evolve over time—such as climate, soil conditions, and irrigation practices. The nine climate zones, defined by the National Oceanic and Atmospheric Administration (NOAA; see Table D5 in *SI Appendix D*) (National Centers for Environmental Information, n.d.), capture long-run differences that shape comparative advantages of agriculture between states and their trading partners. Yet, in some years, origin and/or destination states experience idiosyncratic, short-run weather-induced disruptions—localized shocks that vary across states within the same zone. These disruptions can lead to temporary shifts in crop trade, consistent with patterns observed in a recent meta-analysis on weather conditions and agricultural trade (Magalhães Vital et al., 2022).

Next, we re-estimate the same gravity specification (Eq. 5 in *Materials and Methods*), replacing the overall drought measure with extreme and mild drought. Extreme drought is defined as $\text{SPEI} < -1.3$ and mild drought as $-1.3 \leq \text{SPEI} < 0$ (National Drought Mitigation Center, n.d.). Table D2 (*SI Appendix D*) reports these results in columns 2. We find that a 1% increase in extreme drought in a destination state is associated with a 0.65% increase in imports of vegetables, fruits, and other crops (SCTG 03). For cereal grains (SCTG 02), the negative effect of drought at the origin becomes even more pronounced: a 1% increase in extreme drought leads to a 0.75% reduction in exports. At the same time, extreme drought in a destination state increases cereal grain exports (to destinations) by 0.59%. This is consistent with previous findings that drought reduces local availability and triggers compensatory trade responses. Additional tests using alternative drought thresholds confirm the robustness of these findings, particularly for cereal grains (Fig. E2 in *SI Appendix E*).

4.2. Crops are vital inputs for food manufacturing

Next, we present estimates of the output elasticities of agricultural inputs, capital, and labor based on a production function for manufactured food and beverages. While agricultural inputs are essential for food manufacturing, their supply is simultaneously shaped by demand from the downstream sector, as input use may adjust in response to production incentives. Thus, we implement an instrumental variable (IV) approach and estimate the structural equation for manufactured food production using two-stage least squares (2SLS), as detailed in *Materials and Methods*. We construct instruments derived from a gravity model of trade (Eq. 4) which predicts agricultural input flows based on trade fundamentals and weather shocks. Output elasticities are then estimated based on the observed agricultural inputs instrumented with gravity-based predictions (Eq. 3). The identifying assumption is that local and distant weather shocks affect food manufacturing output in importing states only through its impact on input availability and trade. This approach allows us to capture how weather disruptions in one region influence food manufacturing in another through interstate trade in agricultural inputs.

In *SI Appendix D*, Table D3 reports the first-stage results, and Table D4 reports the second-stage estimates. In each table, column 1 shows estimates using instruments constructed from gravity with drought, while column 2 uses instruments based on extreme and mild drought. The first-stage results indicate that each SCTG-specific instrument is a strong and statistically significant predictor of the corresponding observed agricultural input inflows. In the second stage, we find a significant output elasticity of approximately 0.18 for capital and 0.64 for labor—indicating that labor contributes roughly 3.5 times more to food manufacturing output than capital. Given that food manufacturing is a labor-intensive activity, this result aligns with expectations (Gandhi et al., 2020; Wahdat and Lusk, 2023).

Second, we find statistically significant output elasticities for the grain-based agricultural inputs. The elasticity estimate of cereal grains (SCTG 02) is 0.06. While the elasticity for other crops (SCTG 03) is positive, it is not statistically significant. We believe this reflects the wide variety of products within this category, which may mask a consistent significant effect. The elasticity of animals and fish (SCTG 01) is also not statistically significant. This may reflect both the diverse range of products in SCTG 03 and the fact SCTG 01 are not used as inputs in several major food manufacturing categories, such as animal feed (SCTG 04), milled grains and bakery (SCTG 06), alcoholic beverages (SCTG 08), and tobacco (SCTG 09). Overall, these findings confirm that food and beverage manufacturing relies most heavily on grain-based commodities for its production process (Huang, 2003; Gandhi et al., 2020; Wahdat and Lusk, 2023).

We conduct several robustness checks to assess the validity and consistency of our findings (see *SI Appendix F*). These include alternative specifications of the gravity-based instruments that exclude importer-side variables potentially correlated with food output; an international variant that accounts for foreign trade flows; and a version that includes food sector capital and labor as proxies for input demand. We also re-estimate the second-stage regression while controlling for importer-level food production and population. Finally, we use a narrower definition of food manufacturing output that excludes alcoholic beverages and tobacco, hence focusing on SCTG categories 04–07 only. Across all specifications, the results remain consistent: weather-induced variation in cereal grain trade continues to significantly affect manufactured food output, both under normal and extreme drought conditions (full results are in *SI Appendix F*, Tables F1–F7).

4.3. Impacts of drought on food manufacturing

The remainder of the analysis focuses on the effects of extreme droughts—defined as periods when the SPEI is below –1.3—given their consistent impacts on both domestic exports and imports of cereal grains. To further examine the heterogeneous impacts of extreme weather across states and sectors, this subsection presents a series of maps illustrating intrastate, interstate, and intersectoral spillover effects, beginning with California (CA) and its trading partners, followed by Texas (TX). These two states are highlighted due to their leading roles in U.S. food manufacturing. In addition to CA and TX, the analysis includes a complete set of 48-by-48 estimated pairwise effects of droughts on food manufacturing across the continental United States.

4.4. Local drought and bilateral spillovers

We start by simulating a 100% extreme drought increase on all the grain producing areas of CA and TX. Contrary to basic expectations, this leads to an increase in food manufacturing in each of the two states compared to the 1997–2017 average production level**.** The results are displayed in Figs. 4A and 4B. The key element is in the increase in cereal grains (SCTG 02) imported from other states, notably from the Midwest, which corresponds to a substitution effect. For CA, the mitigation effect of a local drought takes place through importing inputs from Nebraska ($2.8 billion) and Iowa ($1.4 billion) (Fig. 4A). Together, they cover 68% of the total avoided loss, hence they represent key suppliers for CA's food manufacturing sector. When it comes to TX, the food manufacturing losses that are avoided are lower ($3.6 billion vs. $6.2 billion for CA) because the state's food production is lower ($100 billion vs. $173 billion), and its grain production is higher ($8.6 billion vs. $2.6 billion). As in the CA case, the states that mitigate the extreme weather effect in TX are in the Midwest, but they are geographically closer to the destination state. Texas' key players are Kansas ($1.8 billion) and Missouri

($0.4 billion), the two states accounting for 62% of the total avoided loss (Fig. 4B). The analogous map for the vegetables, fruits, and other crops' (SCTG 03) trade network is displayed in Fig. D3 (*SI Appendix D*). Results show that for CA (total loss is $4.1 billion), the key providers are Arizona and Oregon; for TX (total loss is $2.4 billion) they are Nebraska, Oklahoma, and Louisiana. As expected, the key links in the agricultural trade network vary by commodity type and by destination state.

To systematically analyze the substitution effect, we extend our assessment to all state-pair trade relationships. Fig. 5A highlights how the destination states that experience more droughts avoid losses by importing SCTG 02 from producing states. Several key observations stand out. First, we recover the results discussed earlier for CA and TX. Respectively, 78% of the grains that CA would import after a drought and 67% of those TX would import originate from the Midwest. However, for the other states, the degree of substitution and dependence on Midwestern grain suppliers varies. It is high for Michigan (89%), Missouri (81%), Georgia (76%) and Indiana (76%) but much lower for New York (38%), Pennsylvania (47%) or New Jersey (11%). For the latter states, a broader supplier network might enhance their supply chain resilience by providing a greater capacity to shift sourcing when drought disrupts their own production areas. In addition, we discover that their places of import are locally concentrated. Indeed, in case of a drought, these states would primarily source grains from each other or from Ohio. This localized trade dependence is likely supported by major transportation routes, such as Interstate-81 and Interstate-78, which connect their key agricultural areas with food manufacturers, hence promoting a steady supply of grains.

Fig. 5B focuses on SCTG 03 commodities. Based on the two-stage model, we find that the average elasticity of a local drought on food manufacturing after substitution is lower for SCTG 03 (0.036% vs. 0.023% for SCTG 02). This suggests that droughts in destination states prompt a smaller percentage increase in imports of SCTG 03 products, suggesting a more muted response. In terms of loss avoidance flows, the most substantial SCTG 02 flow—Nebraska supplying California—is valued at $2.8 billion, whereas the largest SCTG 03 flow—Arizona supplying California—is $0.6 billion only. Moreover, SCTG 03 suppliers are more geographically dispersed, with no dominant clusters evident in the flow matrix. This broader and more distributed supplier network enhances resilience by enabling destination states to more readily substitute among sources when local droughts disrupt supply.

4.5. Distant drought and bilateral spillovers

Next, Fig. 6 displays the production loss of CA and TX when a 100% increase in extreme drought takes place in the grain (SCTG 02) producing areas of all the other states (we call it the inward effect). This exercise reveals that the key providers are the same as in the previous simulation. Yet, the final effect on food 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 example, for CA the food manufacturing losses would be large at $7.9 billion, $3.6 billion of which due to drought in Nebraska and $1.8 billion in Iowa (Fig. 6A). Similarly, in TX the losses are estimated at $4.5 billion, $2.3 billion of which are due to drought-struck Kansas and $0.5 billion is due to Missouri (Fig. 6B). The analogous map for the vegetable, fruits, and other crops' (SCTG 03) trade network is displayed in Fig. D4 (*SI Appendix D*). The key players are the same as in Fig. D3. We also note that the total loss for each state ($0.7 billion in CA and $0.4 billion in TX) is less than the one due to a drought on SCTG 02 producing areas (in Fig. 6), showing that SCTG 02 plays a greater role in the country's agrifood supply chain than the crops included in SCTG 03 (vegetables, fruits, and soybeans).

The next bilateral simulation presents how a 100% increase in extreme drought in the crop-producing areas of CA and TX leads to a loss in food manufacturing in the rest of the United States (which we refer to as the outward effect). Results for SCTG 02 and SCTG 03 are in *SI Appendix D*, Figs. D5 and D6. For SCTG 02, an event centered in the grain-producing areas of CA would primarily affect food manufacturing in Nevada ($190 million) and Iowa ($67 million), while the same event in TX would affect New Jersey ($439 million) and CA ($187 million). As expected, the outward effect is lower than the inward effect. The reason is that, although CA and TX are the nation's leading food manufacturing states, they play relatively limited role in supplying cereal grains to the rest of the country. A less pronounced loss is observed for SCTG 03 commodities, as shown in Fig D6.

Building on the previous maps, we model both inward and outward effects across all state-pair trade relationships. Fig. 7A illustrates how droughts in grain-producing Midwestern states trigger declines in food manufacturing across a broad range of destination states—demonstrating that significant losses are not confined to CA and TX. The specific vulnerabilities, however, vary by destination. For instance, CA is particularly susceptible to extreme droughts in Nebraska and Iowa, while TX experiences the greatest disruptions when Kansas and Missouri are affected. The cascading effects of drought can also be traced from the origin states. For example, droughts in Indiana result in widespread manufacturing losses across multiple states, including Florida, Georgia, Illinois, and Ohio. In contrast, droughts in Nebraska, Kansas, or Iowa tend to produce more concentrated effects, primarily impacting CA or TX. For states that rely heavily on a narrow set of suppliers, one resilience strategy is to diversify sourcing across multiple counties within top supplying states. This may be particularly effective when droughts are localized but less so in widespread events, such as the 2012 drought. As outlined in more detail in the Discussion section, another policy-relevant strategy involves fostering multi-state coordination to harmonize trade regulations and improve infrastructure, thereby facilitating a faster recovery of inputs supplies following extreme weather disruptions.

Fig. 7B further illustrates that, with the exception of Rhode Island (RI), a drought in any SCTG 03-producing region across the country negatively impacts food manufacturing in all states. However, the extent of these impacts varies and is generally less severe than in the SCTG 02 case. The reason is that the broad geographic dispersion of SCTG 03 suppliers enhances the resilience of the food manufacturing sector. For instance, CA depends heavily on SCTG 03 inputs from Arizona, Nevada, Oregon, Washington, and TX, but the likelihood of simultaneous drought across all these regions is low. RI’s exception is unsurprising, given its small geographic size and the fact that its SCTG 03 products are primarily sold at farmers' markets or distributed through local food systems. By analyzing all pairwise combinations in Fig. 7 and Fig. 5, we provide the first comprehensive map of the interstate dependencies within the U.S. food manufacturing network.

4.6. Local drought and nation-wide impacts

While the preceding analysis highlights key trade linkages, it does not reveal which state-level droughts pose the greatest threat to national food manufacturing. To address this question, we perform two additional simulations—one for each agricultural trade network (SCTG 02 and 03)—evaluating the outward effects of drought from each of the 48 continental states. This approach enables us to identify where the vulnerabilities of the nationwide food system lie.

Building on the outward effects (Figs. D5 and D6 in *SI Appendix D*), we find that national food manufacturing is most sensitive to droughts in Midwestern states, which are major grain (SCTG 02) producers. In addition, Fig. D7A shows that the most severe losses are associated with extreme droughts in SCTG 02-producing areas of Nebraska ($7.5 billion), Indiana ($6.3 billion), and Illinois ($5.4 billion). A similar pattern emerges for vegetables, fruits and other crop (SCTG 03) commodities in Fig. D7B, where the most pronounced impacts originate from droughts in the West, South, and Corn Belt—particularly Illinois, Iowa, and Nebraska. Although these states are not traditionally recognized for fruit and vegetable production, the explanation lies in soybean production, which is included in SCTG 03. Notably, 70% of soybean production is used for animal feed, a key component of the nation's food manufacturing sector (*USDA Coexistence Fact Sheets - Soybeans*, 2015).

5. Discussion

This study offers critical insights into how climate-driven disruptions—especially droughts—propagate through the U.S. agrifood supply chain. With a two-stage empirical framework that links extreme weather events to changes in interregional trade and downstream food manufacturing output, we move beyond farm-level analysis and offer a system-wide understanding of vulnerability and resilience. The results show that while food manufacturing is not directly exposed to weather events due to its indoor nature, its dependence on geographically distributed agricultural inputs creates systemic exposure to upstream production shocks.

Our findings reveal that, on average, a 1% increase in drought in commodity-producing states leads to a 0.5–0.7% decline in agricultural exports to other states and a corresponding 0.04% reduction in food manufacturing output. The aggregate effects are mitigated by key resilience mechanisms—namely, the ability of states to substitute inputs across regions, maintain redundancy in their sourcing networks, and adapt sourcing patterns in response to evolving conditions. These mechanisms reflect the system's inherent robustness but also underscore its dependence on functional transportation corridors, diverse supplier networks, and timely trade adjustments.

These findings yield several implications for policy and practice. First, infrastructure investment decisions can be guided by the identification of critical trade corridors—such as shipments from Nebraska and Iowa to California or from Kansas to Texas. Targeted investments in rail, highways, and intermodal hubs that support these corridors can improve the reliability and climate resilience of national food supply chains. Second, state governments—particularly those in high-dependence or high-supply regions—can use the bilateral dependency matrices developed in this study to support the formation of multi-state resilience plans. Such plans may include shared storage reserves, pre-negotiated emergency procurement protocols, and harmonized trade regulations during times of crisis. In particular, Midwestern states that are top suppliers of cereal grains and other key crops could enter into resilience pacts with major manufacturing states to ensure continuity of supply under stress.

Third, our results have direct implications for reforming crop insurance and disaster relief programs. Currently, crop insurance and disaster relief are typically allocated based on where the shock physically occurs. The findings in this paper argue for expanding the eligibility criteria to include indirectly affected states that experience food production shortfalls due to supply chain disruptions. For example, New Jersey's food manufacturers may be eligible for partial compensation or support when a drought in Kansas cuts off grain supplies. Agencies such as United States Department of Agriculture (USDA) and Federal Emergency Management Agency (FEMA) can use this evidence to design network-sensitive compensation mechanisms and insurance products that better reflect interdependence in the food system.

Fourth, the maps and simulations in the study show how manufacturing states reliant on a narrow set of suppliers (e.g., California's dependence on Nebraska and Iowa for cereal grains) are more vulnerable to disruption. As a result, firms can use these insights to diversify their supplier networks by sourcing inputs from a broader and more geographically dispersed set of states. Procurement officers can also use the pairwise elasticity estimates to evaluate the value of long-term contracts, supply redundancy, or investment in local supplier development. This kind of supply chain restructuring—when informed by state-level trade sensitivity and substitution elasticity—can significantly enhance firm-level resilience and reduce business continuity risks.

Fifth, our framework can serve as the basis for a subnational food resilience index—akin to the Food and Agriculture Organization's (FAO) Dietary Sourcing Flexibility Index. Such a tool would synthesize sourcing diversity, trade exposure, and drought sensitivity into a single measure that could be integrated into early-warning systems and strategic planning dashboards. Emergency managers, logistics coordinators, and regional planning agencies could use such an index to anticipate bottlenecks and adjust sourcing in advance of disruptions.

Finally, the study provides a foundation for refining national strategic reserve policies. Currently centered around population or consumption metrics, these reserves could be repositioned to reflect the trade-mediated vulnerabilities of major food manufacturing hubs. For example, if Nebraska or Kansas experiences a widespread drought, reserve stocks could be mobilized rapidly to states like California that would otherwise face severe shortfalls in manufacturing inputs. By identifying the key upstream dependencies of these hubs, decision-makers can determine where and how much reserve capacity is needed in specific locations to offset projected losses under plausible future drought scenarios. Over time, these targeted reserves would increase systemwide robustness and allow for faster recovery from disruptions that ripple across state lines.

In sum, this research not only advances the empirical understanding of climate shocks in food supply chains but also offers a practical, data-driven foundation for improving infrastructure planning, supply chain design, emergency preparedness, and long-term climate adaptation. As extreme weather events become more frequent and intense, leveraging these insights to inform coordinated, multi-scale responses will be essential to maintaining food security and economic stability across the United States.

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 the trade flows to the commodity level, as has been done for corn (27), but while accounting for formal microeconomic foundations and the role of drought and wetness like we have done here. In addition, we intend to consider other weather events, such as early frost and hail, and rely on future climate conditions to estimate how future agrifood trade flows may evolve in response.

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References

Anderson, J. E., and van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, *93*(1), 170–192. https://doi.org/10.1257/000282803321455214

Anderson, J. E., and Yotov, Y. V. (2016). Terms of trade and global efficiency effects of free trade agreements, 1990-2002. *Journal of International Economics*, *99*, 279–298. https://doi.org/10.1016/j.jinteco.2015.10.006

Baier, S. L., and Bergstrand, J. H. (2009). Bonus vetus OLS: A simple method for approximating international trade-cost effects using the gravity equation. *Journal of International Economics*, *77*(1), 77–85. https://doi.org/10.1016/j.jinteco.2008.10.004

Baldos, U. L. C., and Hertel, T. W. (2015). The role of international trade in managing food security risks from climate change. *Food Security*, *7*(2), 275–290. https://doi.org/10.1007/s12571-015-0435-z

Barrett, C. B., Benton, T. G., Cooper, K. A., Fanzo, J., Gandhi, R., Herrero, M., James, S., Kahn, M., Mason-D'Croz, D., Mathys, A., Nelson, R. J., Shen, J., Thornton, P., Bageant, E., Fan, S., Mude, A. G., Sibanda, L. M., and Wood, S. (2020). Bundling innovations to transform agri-food systems. *Nature Sustainability*, *3*(12), 974–976. https://doi.org/10.1038/s41893-020-00661-8

Battisti, D. S., and Naylor, R. L. (2009). Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat. *Science*, *323*(5911), 240–244.

Beckman, J., Dyck, J., and Heerman, K. E. R. (2017). The Global Landscape of Agricultural Trade, 1995-2014. *U.S. Department of Agriculture*, *EIB-181*.

Bertassello, L., Winters, P., and Müller, M. F. (2023). Access to global wheat reserves determines country-level vulnerability to conflict-induced Ukrainian wheat supply disruption. *Nature Food*, *4*(8), 673–676. https://doi.org/10.1038/s43016-023-00806-w

Cheng, M., McCarl, B., and Fei, C. (2022). Climate Change and Livestock Production: A Literature Review. *Atmosphere*, *13*(1).

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, *124*(1), 205–248. https://doi.org/10.1086/684719

Dall'erba, S., Chen, Z., and Nava, N. J. (2021). U.S. Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit. *American Journal of Agricultural Economics*, *103*(5), 1720–1741. https://doi.org/10.1111/ajae.12204

Dall'erba, S., Ridley, W., Zou, J., and Youning, C. (2025). *Statistical downscaling of the US food supply-chain [Preprint]*. https://ageconsearch.umn.edu/record/343526

Davis, K. F., Downs, S., and Gephart, J. A. (2021). Towards food supply chain resilience to environmental shocks. *Nature Food*, *2*(1), 54–65. https://doi.org/10.1038/s43016-020-00196-3

Dorn, F., Fuest, C., and Potrafke, N. (2022). Trade openness and income inequality: New empirical evidence. *Economic Inquiry*, *60*(1), 202–223. https://doi.org/10.1111/ecin.13018

Escarcha, J. F., Lassa, J. A., and Zander, K. K. (2018). Livestock under climate change: A systematic review of impacts and adaptation. *Climate*, *6*(3), 1–17. https://doi.org/10.3390/cli6030054

Fanzo, J., Haddad, L., Schneider, K. R., Béné, C., Covic, N. M., Guarin, A., Herforth, A. W., Herrero, M., Sumaila, U. R., Aburto, N. J., Amuyunzu-Nyamongo, M., Barquera, S., Battersby, J., Beal, T., Bizzotto Molina, P., Brusset, E., Cafiero, C., Campeau, C., Caron, P., … Rosero Moncayo, J. (2021). Viewpoint: Rigorous monitoring is necessary to guide food system transformation in the countdown to the 2030 global goals. *Food Policy*, *104*. https://doi.org/10.1016/j.foodpol.2021.102163

Felbermayr, G., and Gröschl, J. (2013). Natural disasters and the effect of trade on income: A new panel IV approach. *European Economic Review*, *58*, 18–30. https://doi.org/10.1016/j.euroecorev.2012.11.008

Ferguson, S. M., and Gars, J. (2020). Measuring the impact of agricultural production shocks on international trade flows. *European Review of Agricultural Economics*, *47*(3), 1094–1132. https://doi.org/10.1093/erae/jbz013

Feyrer, J. (2019). Trade and income-exploiting time series in geography. *American Economic Journal: Applied Economics*, *11*(4), 1–35. https://doi.org/10.1257/app.20170616

Frankel, J. A., and Romer, D. (1999). Does Trade Cause Growth? *American Economic Review*, *89*(3), 379–399. https://doi.org/10.4324/9781315254166-11

FRB Estimates of Manufacturing Investment, Capital Stock, and Capital Services. (2023). Federal Reserve Board. https://www.federalreserve.gov/releases/g17/related_data/manuf_invest_capital.htm

Freight Analysis Framework, FAF5. (2017). U.S. Department of Transportation, Bureau of Transportation Statistics, Federal Highway Administration. https://www.bts.gov/faf

Gandhi, A., Navarro, S., and Rivers, D. A. (2020). On the identification of gross output production functions. *Journal of Political Economy*, *128*(8), 2973–3016. https://doi.org/10.1086/707736

Garofalo, G. A., and Yamarik, S. (2002). Regional Convergence: Evidence from a New State-by-State Capital Stock Series. *The Review of Economics and Statistics*, *84*(2), 316–323. https://www.jstor.org/stable/3211780

Gaupp, F., Hall, J., Hochrainer-Stigler, S., and Dadson, S. (2020). Changing risks of simultaneous global breadbasket failure. *Nature Climate Change*, *10*(1), 54–57. https://doi.org/10.1038/s41558-019-0600-z

Gouel, C., and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, *106*(102408), 1–26. https://doi.org/10.1016/j.jeem.2020.102408

Head, K., and Mayer, T. (2014). Chapter 3 - Gravity Equations: Workhorse, Toolkit, and Cookbook. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of*

International Economics, (pp. 131–195).

Huang, K. S. (2003). Food Manufacturing Productivity and Its Economic Implications. *U.S. Department of Agriculture*, *TB-1905*(TB-1905). https://www.ers.usda.gov/publications/pub-details/?pubid=47446

Hwang, H.-L., Lim, H., Chin, S.-M., Uddin, M., Biehl, A., Xie, F., Hargrove, S., Liu, Y., and Wang, C. (2021). Freight Analysis Framework Version 5 (FAF5) Base Year 2017 Data Development Technical Report. *U.S. Department of Energy, Oak Ridge National Laboratory, 5*. https://rosap.ntl.bts.gov/view/dot/68154

Iizumi, T., and Ramankutty, N. (2015). How do weather and climate influence cropping area and intensity? *Global Food Security*, *4*, 46–50. https://doi.org/10.1016/j.gfs.2014.11.003

Implicit Price Deflators for Gross Domestic Product. (2023). Bureau of Economic Analysis. https://apps.bea.gov/iTable/?reqid=19&step=2&isuri=1

Inoue, H., and Todo, Y. (2019). Firm-level propagation of shocks through supply-chain networks. *Nature Sustainability*, *2*(9), 841–847. https://doi.org/10.1038/s41893-019-0351-x

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability* (H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama (Eds.); H.-O. Pört). Cambridge University Press.

Jagermeyr, J., Robock, A., Elliott, J., Muller, C., Xia, L., Khabarov, N., Folberth, C., Schmid, E., Liu, W., Zabel, F., Rabin, S. S., Puma, M. J., Heslin, A., Franke, J., Foster, I., Asseng, S., Bardeen, C. G., Toon, O. B., and Rosenzweig, C. (2020). A regional nuclear conflict would compromise global food security. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(13), 7071–7081. https://doi.org/10.1073/pnas.1919049117

Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B., and Vail, P. (2019). Estimating the impact of drought on agriculture using the U.S. Drought Monitor. *American Journal of Agricultural Economics*, *101*(1), 193–210. https://doi.org/10.1093/ajae/aay037

Laber, M., Klimek, P., Bruckner, M., Yang, L., and Thurner, S. (2023). Shock propagation from the Russia–Ukraine conflict on international multilayer food production network determines global food availability. *Nature Food*, *4*(6), 508–517. https://doi.org/10.1038/s43016-023-00771-4

Lesk, C., Rowhani, P., and Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84–87. https://doi.org/10.1038/nature16467

Lin, X., Ruess, P. J., Marston, L., and Konar, M. (2019). Food flows between counties in the United States. *Environmental Research Letters*, *14*(8), 1–17. https://doi.org/10.1088/1748-9326/ab29ae

Maestas, B. N., Mullen, K. J., and Powell, D. (2023). The Effect of Population Aging on Economic Growth, the Labor Force, and Productivity. *American Economic Journal: Macroeconomics*, *15*(2), 306–332.

Magalhães Vital, T., Dall'erba, S., Ridley, W., and Wang, X. (2022). What do the 235 estimates from the literature tell us about the impact of weather on agricultural and food trade flows? *Global Food Security*, *35*(100654), 1–11. https://doi.org/10.1016/j.gfs.2022.100654

Malik, A., Li, M., Lenzen, M., Fry, J., Liyanapathirana, N., Beyer, K., Boylan, S., Lee, A., Raubenheimer, D., Geschke, A., and Prokopenko, M. (2022). Impacts of climate change and extreme weather on food supply chains cascade across sectors and regions in Australia. *Nature Food, 3*(8), 631–643. https://doi.org/10.1038/s43016-022-00570-3

Marchand, P., Carr, J. A., Dell'Angelo, J., Fader, M., Gephart, J. A., Kummu, M., Magliocca, N. R., Porkka, M., Puma, M. J., Ratajczak, Z., Rulli, M. C., Seekell, D. A., Suweis, S., Tavoni, A., and D'Odorico, P. (2016). Reserves and trade jointly determine exposure to food supply shocks. *Environmental Research Letters*, *11*(9), 095009. https://doi.org/10.1088/1748-9326/11/9/095009

Mayer, T., and Head, K. (2002). Illusory border effects: Distance mismeasurement inflates estimates of home bias in trade. *CEPII Working Paper No 2002-01,* 1–32.

Millard, C. (2019). From Farm to Table: Supporting Local Food Supply Chains through Transportation Investments. Public Roads, Summer 2019. *Federal Highway Administration*. https://highways.dot.gov/public-roads/summer-2019/farm-table

Moser, S., Meerow, S., Arnott, J., and Jack-Scott, E. (2019). The turbulent world of resilience: interpretations and themes for transdisciplinary dialogue. *Climatic Change*, *153*(1–2), 21–40. https://doi.org/10.1007/s10584-018-2358-0

National Centers for Environmental Information. (n.d.). *U.S. Climate Regions*. National Oceanic and Atmospheric Administration (NOAA). https://www.ncei.noaa.gov/access/monitoring/reference-maps/us-climate-regions

National Drought Mitigation Center. (n.d.). *Drought Classification - U.S. Drought Monitor*. University of Nebraska-Lincoln. https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx.

Nava, N. J., Ridley, W., and Dall'erba, S. (2023). A model of the U.S. food system: What are the determinants of the state vulnerabilities to production shocks and supply chain disruptions? *Agricultural Economics*, *54*(1), 95–109. https://doi.org/10.1111/agec.12750

Peri, G. (2012). The Effect Of Immigration On Productivity: Evidence From U.S. States. *The Review of Economics and Statistics*, *94*(1), 348–358. https://doi.org/10.1162/REST_a_00137

Population and Housing Unit Estimates Tables. (2023). U.S. Census Bureau. https://www.census.gov/programs-surveys/popest/data/tables.html

Producer Price Index program staff. (2012). Will the 2012 drought have a bigger impact on grocery prices than the 1988 drought? Beyond the Numbers: Prices & Spending. *U.S. Bureau of Labor Statistics*. https://www.bls.gov/opub/btn/volume-1/will-the-2012-drought-have-a-bigger-impact-on-grocery-prices-than-the-1988-drought.htm

Rathore, L. S., Kumar, M., McNider, R. T., Magliocca, N., and Ellenburg, W. (2024). Contrasting corn acreage trends in the Midwest and Southeast: The role of yield, climate, economics, and irrigation. *Journal of Agriculture and Food Research*, *18*(July), 101373. https://doi.org/10.1016/j.jafr.2024.101373

Ray, R. L., Fares, A., and Risch, E. (2018). Effects of Drought on Crop Production and Cropping Areas in Texas. *Agricultural & Environmental Letters*, *3*(1), 1–5. https://doi.org/10.2134/ael2017.11.0037

Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., Bowen, S. G., Camargo, S. J., Hess, J., Kornhuber, K., Oppenheimer, M., Ruane, A. C., Wahl, T., and White, K. (2020). Understanding and managing connected extreme events. *Nature Climate Change*, *10*(7), 611–621. https://doi.org/10.1038/s41558-020-0790-4

Regional Data GDP and Personal Income. (2023). Bureau of Economic Analysis. https://apps.bea.gov/itable/?ReqID=70&step=1&acrdn=1

Rushforth, R. R., and Ruddell, B. L. (2018). A spatially detailed blue water footprint of the United States economy. *Hydrology and Earth System Sciences*, *22*(5), 3007–3032. https://doi.org/10.5194/hess-22-3007-2018

Rutten, M., Shutes, L., and Meijerink, G. (2013). Sit down at the ball game: How trade barriers make the world less food secure. *Food Policy*, *38*(1), 1–10. https://doi.org/10.1016/j.foodpol.2012.09.002

Sanderson, E., and Windmeijer, F. (2016). A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics*, *190*(2), 212–221. https://doi.org/10.1016/j.jeconom.2015.06.004

Santos Silva, J. M. C., and Tenreyro, S. (2006). The Log of Gravity. *The Review of Economics and Statistics*, *88*(4), 641–658. https://www.jstor.org/stable/40043025

Santos Silva, J. M. C., and Tenreyro, S. (2011). Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator. *Economics Letters*, *112*(2), 220–222. https://doi.org/10.1016/j.econlet.2011.05.008

Schimmelpfennig, D., Lewandrowski, J., Reilly, J., Tsigas, M., and Parry, I. (1996). Agricultural Adaptation to Climate Change: Issues of Long Range Sustainability. *U.S. Department of Agriculture Natural Resources and Environment Division, Economic Research Service., AER-740*. https://www.ers.usda.gov/publications/pub-details/?pubid=40714

Schmidhuber, J., and Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(50), 19703–19708. https://doi.org/10.1073/pnas.0701976104

Smith, T. M., Goodkind, A. L., Kim, T., Pelton, R. E. O., Suh, K., and Schmitt, J. (2017). Subnational mobility and consumption-based environmental accounting of US corn in animal protein and ethanol supply chains. *Proceedings of the National Academy of Sciences*, *114*(38), E7891–E7899. https://doi.org/10.1073/pnas.1703793114

Soybeans - Production. (2023). U.S. Department of Agriculture. https://quickstats.nass.usda.gov/

Staiger, D., and Stock, J. H. (1997). Instrumental Variables Regression with Weak Instruments. *Econometrica*, *65*(3), 557. https://doi.org/10.2307/2171753

Stock, J. H., and Yogo, M. (2002). Testing for Weak Instruments in Linear IV Regression. *National Bureau of Economic Research*, *T0284*.

Szewerniak, W. W., Xu, Y., and Dall'erba, S. (2019). The effects of diesel price on regional trade in the USA. *Journal of Economic Geography*, *19*(5), 1099–1118. https://doi.org/10.1093/jeg/lby052

Tendall, D. M., Joerin, J., Kopainsky, B., Edwards, P., Shreck, A., Le, Q. B., Kruetli, P., Grant, M., and Six, J. (2015). Food system resilience: Defining the concept. *Global Food Security*, *6*, 17–23. https://doi.org/10.1016/j.gfs.2015.08.001

USDA Coexistence Fact Sheets - Soybeans. (2015). U.S. Department of Agriculture. https://www.usda.gov/sites/default/files/documents/coexistence-soybeans-factsheet.pdf

Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., Meinshausen, N., and Frieler, K. (2019). The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, *14*(5), 054010. https://doi.org/10.1088/1748-9326/ab154b

Wahdat, A. Z., and Lusk, J. L. (2023). The Achilles heel of the U.S. food industries: Exposure to labor and upstream industries in the supply chain. *American Journal of Agricultural Economics*, *105*(2), 624–643. https://doi.org/10.1111/ajae.12331

Yamarik, S. (2013). State-level capital and investment: Updates and implications. *Contemporary Economic Policy*, *31*(1), 62–72. https://doi.org/10.1111/j.1465-7287.2011.00282.x

Yotov, Y. V. (2022). On the role of domestic trade flows for estimating the gravity model of trade. *Contemporary Economic Policy*, *40*(3), 526–540. https://doi.org/10.1111/coep.12567

Yotov, Y. V., Piermartini, R., Monteiro, J.-A., and Larch, M. (2016). *An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model*. World Trade Organization.

Figures and Tables

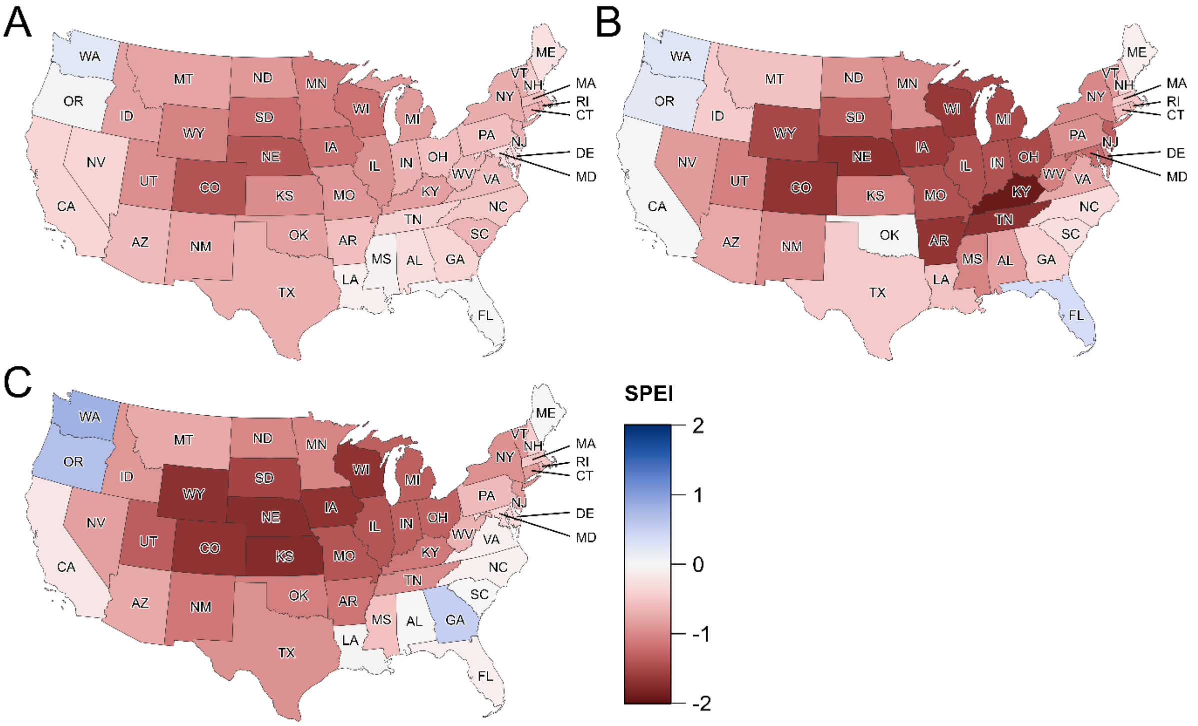

Fig. 1. Drought and wetness by state, 2012. Drought and wetness over (A) animals and fish (B) grains (C) non-grain crops (including vegetables, fruits, and soybeans) producing areas. Each map shows drought (red, negative values) and wetness (blue, positive values) as measured by the Standardized Precipitation Evapotranspiration Index (SPEI).

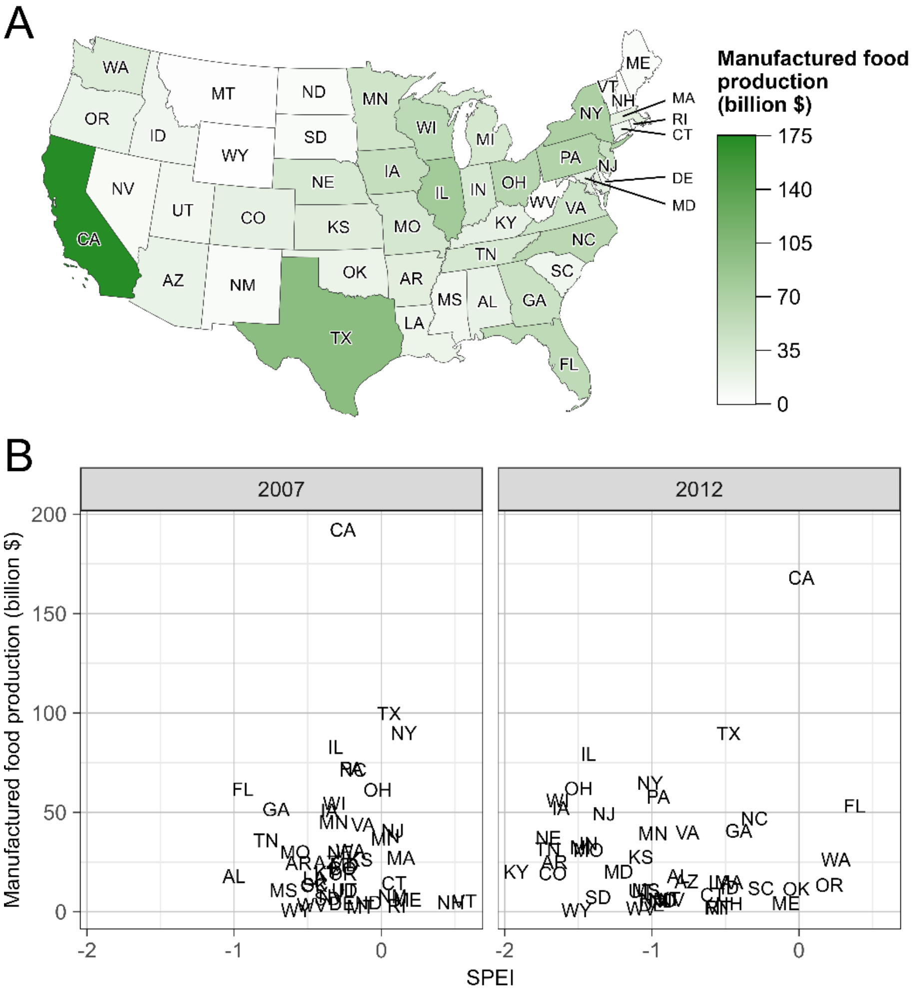

Fig. 2. Production of manufactured food and SPEI by state. (A) The value of total production of food and beverage manufacturing is shown as 1997–2017 average. (B) Scatter plot of the production of food manufacturing (y-axis) and SPEI (x-axis) for 2007 and 2012. Food manufacturing production is calculated as the sum of intrastate and interstate outflows to other U.S. states for the sectors SCTG04-09 in 2012 dollars.

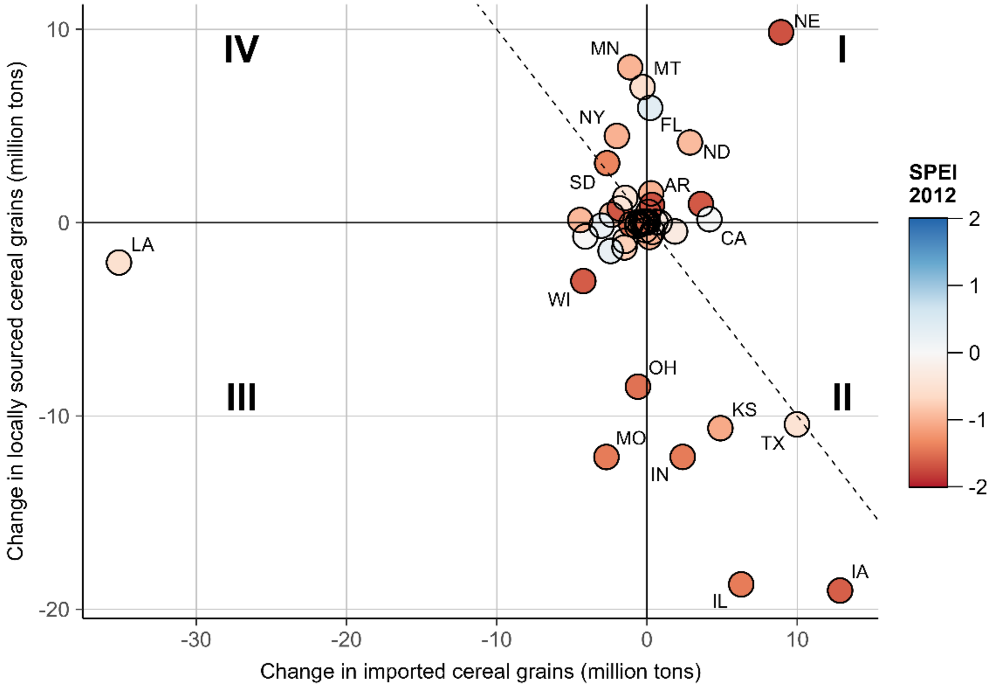

Fig. 3. Scatter plot showing the change in volume of locally sourced (y-axis) and imported (x-axis) cereal grains (SCTG 02) from 2007 to 2012. Point colors represent the SPEI in 2012, with negative values (in red) indicating drought and positive values (in blue) indicating wetness. States above the $y = -x$ (dashed) line have a net increase in SCTG 02 compared to 2007, while those below it experienced a net decrease. States lie in one of the four planes based on the direction of change in local and imported volumes: plane 1 includes 13 states that increased both local and imported SCTG 02, plane 2 shows 8 states that increased imports but decreased local purchases, plane 3 includes 13 states that reduced both sources, while plane 4 includes 14 states that decreased imports but increased local inputs.

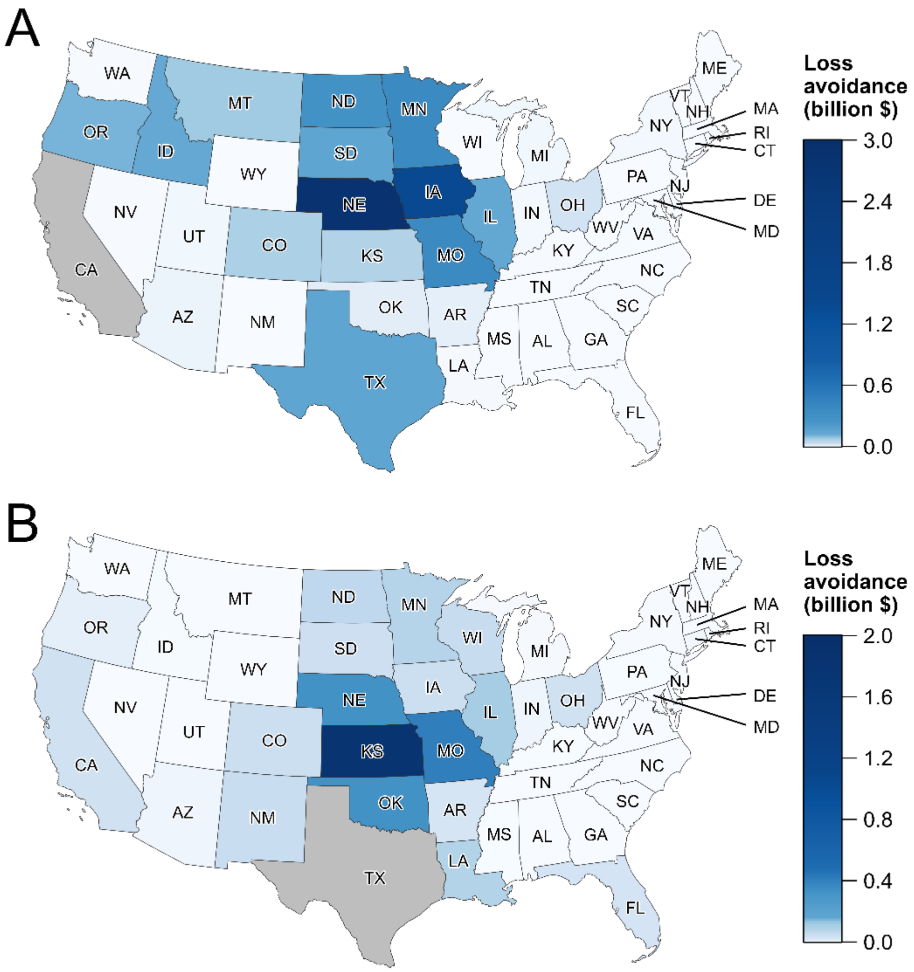

Fig. 4. Loss avoidance in food manufacturing in California (A) and Texas (B) following a 100% drought increase on local cereal grain (SCTG 02) producing areas (gray). The color code corresponds to the production losses California (or Texas) avoided by increasing SCTG 02 imports from origin states (colored). The darker the color, the higher the avoided loss. Estimates and standard errors are in *SI Appendix D*, Table D8.

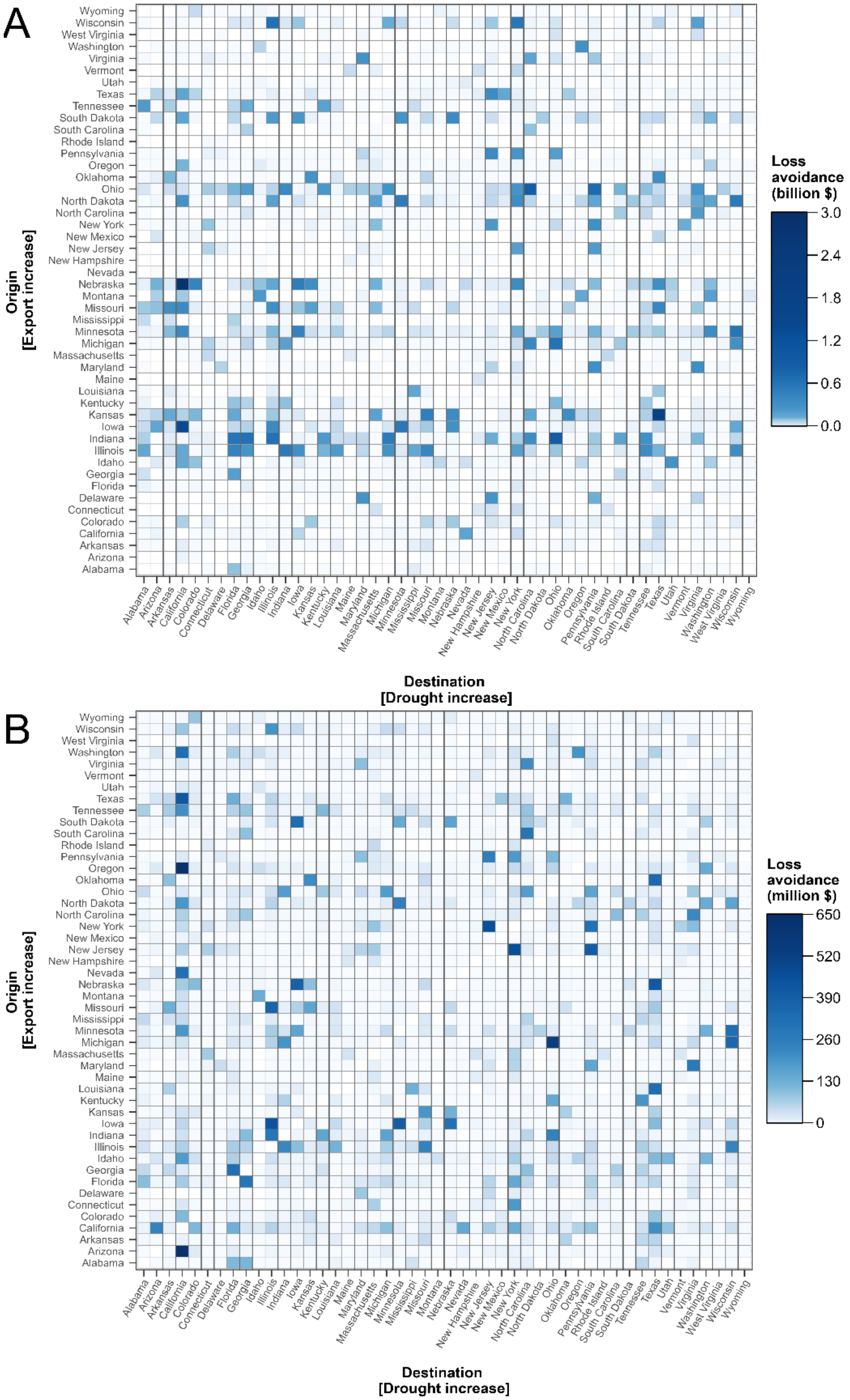

Fig. 5. Loss avoidance in food manufacturing of the destination state following a 100% drought increase on local SCTG 02 (A) and 03 (B) producing areas. SCTG 02 includes cereal grains, and 03 includes vegetables, fruits, and other crops. The colors represent the production losses that the destination states (x-axis) avoided by increasing crop imports from the origin states (y-axis). The darker the color, the higher the avoided loss.

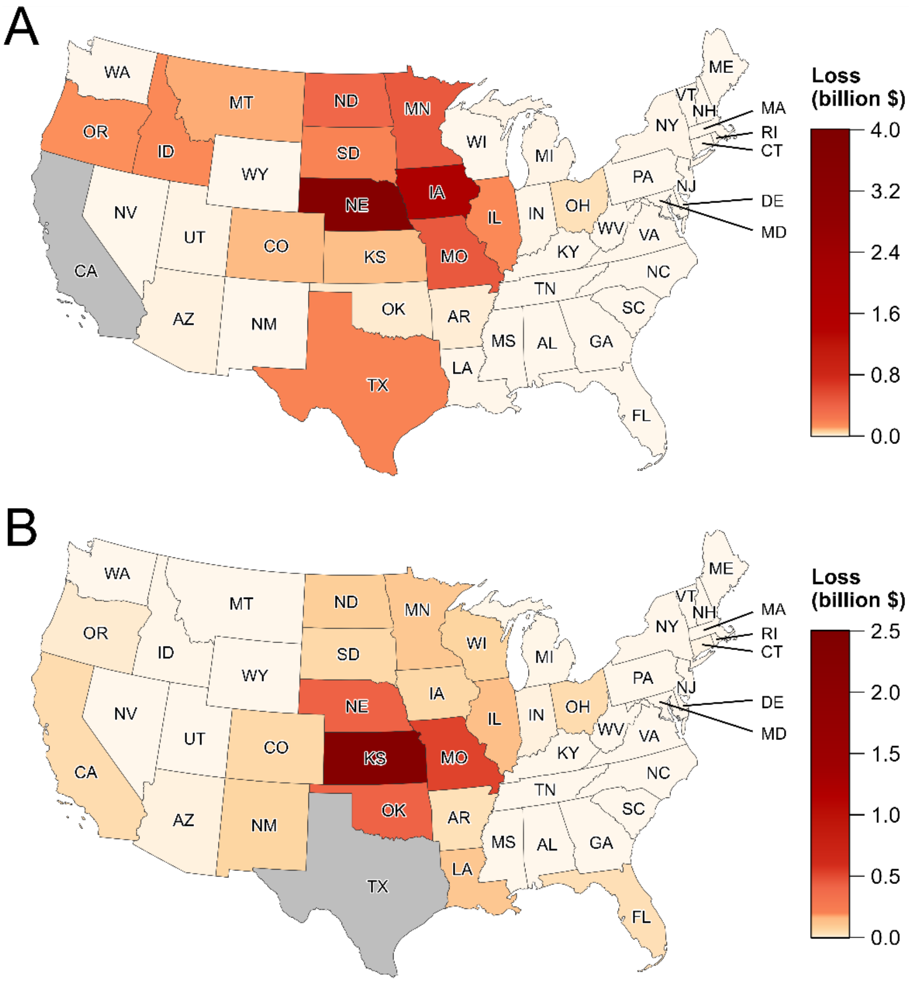

Fig. 6. Loss in food manufacturing in California (A) and Texas (B) following a 100% drought increase on the SCTG 02 producing areas of the origin states (colored). The colors represent the extent to which California (or Texas) food manufacturing production decreases following a drought in each of the colored states from which it imports SCTG 02 commodities. Estimates and standard errors are in *SI Appendix D*, Table D9.

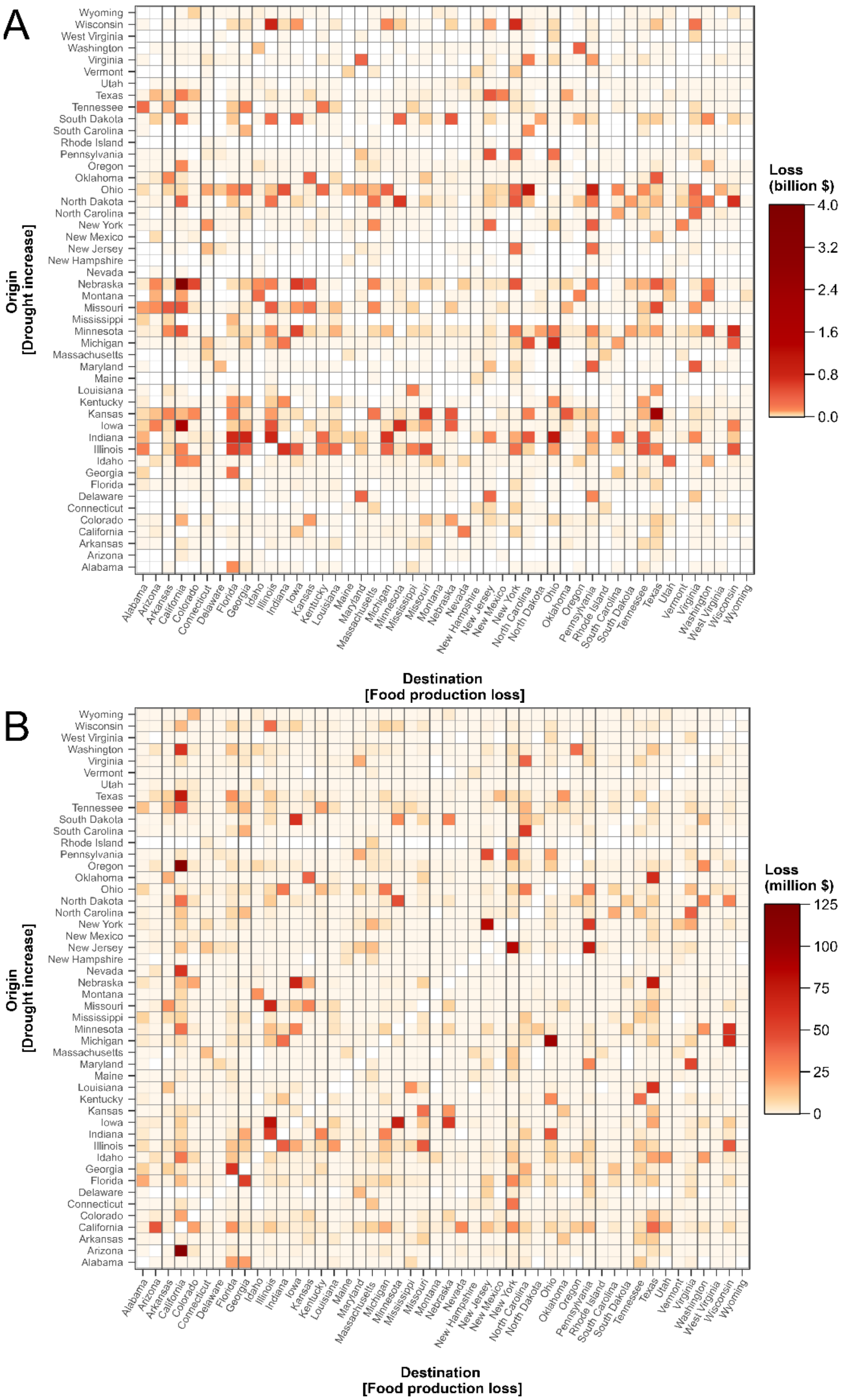

Fig. 7. Loss in food manufacturing in destination states following a 100% drought increase on the SCTG 02 (A) and 03 (B) producing areas of origin states. SCTG 02 includes cereal grains, and 03 includes vegetables, fruits, and other crops. The colors represent the extent to which food manufacturing production in the destination states (x-axis) decreases following a drought in each of the origin states (y-axis) from which it imports crops.

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

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This file includes:

Appendix A. Data

A1. Freight Analysis Framework (FAF) trade data

We choose the FAF over another interstate trade data set, the Commodity Flow Survey (CFS), for several reasons. First, the CFS is collected by surveying shipping firms in the 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 Bureau of Transportation Statistics (BTS) puts together the CFS responses and the missing information from U.S. Department of Agriculture'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 the Standard Industrial Classification (SIC).

A2. Data on extreme and normal weather

The Standardized Precipitation Evapotranspiration Index (SPEI) is computed with weather data obtained from the ERA5-Land database (Muñoz-Sabater et al., 2021). While we recognize that U.S.-specific products like NLDAS, PRISM, HRRR, and Daymet offer higher spatial resolution and may be optimized for CONUS-only studies, ERA5-Land provided several distinct advantages for our specific needs. The primary motivation for using ERA5-

Land is its long-term historical coverage (1950–present). This feature makes it well-suited for capturing long-term trends relevant to our study, especially in computing the SPEI. To calculate the SPEI we obtain the surface temperature and precipitation from the ERA5-Land and calculate the potential evapotranspiration (PET). To attain a standardized PET indicator, we calculate the standardized anomaly as a deviation from the locality's historical distribution (1950–2014) (Thrasher et al., 2022). While PRISM does provide precipitation and temperature data for the United States dating back to 1895 for monthly data, we are concerned that its performance can vary in mountainous regions or remote areas as it depends on ground-station networks for accuracy (PRISM Climate Group, 2024). On the other hand, ERA5-Land data come from a globally consistent reanalysis system that integrates satellite observations and advanced numerical models (Muñoz-Sabater et al., 2021). This comprehensive framework is designed to generate a continuous and complete record of climate variables, filling gaps where direct ground measurements are sparse.

We use the ERA5-Land data base to first 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. Growing season is defined as the middle date of the planting period (the start date of the growing season) and of the harvesting period (as the end date) of all the products within the SCTG 02 and SCTG 03 categories. Since each category includes various crops, the start and end date of each crop's growing season are weighted by each state's farmland area devoted to each crop. The usual planting and harvesting dates of each commodity come from the USDA ("Usual Planting and Harvesting Dates for US Fields Crops," 2010). For SCTG 01, we used year-long SPEI values since there is no growing season for animals and fish.

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. The weights are based on the farmland area of each product classified in SCTG 02/03 from the USDA Farmland Service Agency (*Crop Acreage Data*, 2022). For SCTG 01, we used information on county-level total sales of each livestock product from the USDA NAAS Census of Agriculture (*Soybeans - Production*, 2023). SCTG 01 also includes fish. However, livestock accounts for the largest share of output and intermediate input demand for the manufactured food and beverage sector according to the Input-Output Table D1 in *Appendix D*. 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 grown and harvested in. For the weather controls, we aggregate daily, county-level GDD and precipitation to the annual, state level using the same spatial and temporal weights for each agricultural commodity as for drought and wetness.

A3. Labor

The data on labor is provided for each of the two manufacturing industries: food manufacturing, and beverage and tobacco manufacturing. Several challenges emerged when constructing the state level labor data, especially for beverage and tobacco manufacturing. Undisclosed data is one of these challenges even if the undisclosed values for labor can be easily recovered for some states (e.g., South Dakota and Vermont) by taking the difference between the total values of the upper regions and the sum of the rest. The upper region for South Dakota is the Plains, and it is New England for Vermont. If multiple states report missing employment values, we use the historical ratio between a state's employment and the corresponding upper region's employment. For instance, the reference period for Delaware is

1999–2000 while it is 1998-2007 for Mississippi. 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, an assumption that is verified on the states for which we do have all complete data.

For the year 1997 for which all the data are missing, employment data at the state level is generated using a concordance from the SIC to the NAICS following the approach of previous literature (Peri, 2012). The concordance report is from the U.S. Census Bureau (*Bridge Between 2002 NAICS and 1997 NAICS: 2002*, 2006), and employment for the SIC industries in 1997 is from the Bureau of Economic Analysis (BEA). In the concordance, the 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 food industry's value added from the BEA to NAICS 311 and NAICS 312 using the rate calculated with the SIC-NAICS concordance. 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. As a result, we use the average of the nearest three years for these states.

Appendix B. Estimable equation of the gravity model

Gravity framework of agricultural trade. Agricultural inputs that enter the manufactured food production process require from us to distinguish local from imported inputs. We do this by relying on a state-to-state structural gravity model of trade (Anderson and van Wincoop, 2003; Anderson and Yotov, 2016):

$$I_{ijt}^{AF} = \frac{X_{it}^{A} Y_{jt}^{F}}{X_t} \left(\frac{t_{ijt}}{\Pi_{it} \mathrm{P}_{jt}} \right)^{1-\sigma_\rho}, \qquad \text{[B1]}$$

where I_{ij}^{AF} is the interstate trade of agricultural commodities from origin state i used by destination state j for food manufacturing in year t; X_{it}^{A} is the production of agriculture in the exporting state i; Y_{jt}^{F} is the total expenditure of the manufactured food sector in importing state j while $X_t = \sum_i X_{it} = \sum_j Y_{jt}$ is total agricultural output.

The second elements of Eq. B1 represent bilateral t_{ijt} and multilateral trade frictions for the exporting (Π_{it}) and importing (P_{jt}) state. Bilateral factors 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) represent the state's ease or impediment to market access defined as:

$$\Pi_{it}^{1-\sigma_\rho} = \sum_j \left(\frac{t_{ijt}}{P_{jt}} \right)^{1-\sigma_\rho} \frac{Y_{jt}}{X_t}, \qquad \text{[B2a]}$$

$$P_{jt}^{1-\sigma_\rho} = \sum_i \left(\frac{t_{ijt}}{\Pi_{it}}\right)^{1-\sigma_\rho} \frac{X_{it}}{X_t}, \qquad \text{[B2b]}$$

where 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 Eq. 2 (in the main manuscript): while σ_ρ in the gravity model captures the substitution between all possible destinations of the exporting states, the substitution σ_k in Eq. 2 captures the interaction between local versus imported inputs only.

Within the gravity framework, we consider the situation where an extreme weather event affects the exporting state i and/or the importing state j. Food manufacturing activities take place indoors and thus are not subject to a direct detrimental effect of weather. However, 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, and on the demand for agricultural commodities to be used as intermediate inputs for manufactured food or to be consumed by households. The expected impact of extreme weather shocks on I_{ijt}^{AF} has been well documented (Lesk et al., 2016; Escarcha et al., 2018; Ray et al., 2018; Dall'erba et al., 2021): for the exporters of agricultural goods, production losses following a weather shock would mean less available output to be exported and/or relying on stocks for exports. For importers, production losses following a shock are substituted with imports, hence creating trade.

To econometrically estimate this gravity relationship, we specify an estimable equation for each agricultural commodity k:

$$I_{ijt}^{AF} = \exp\left\{a + \ln X_{it}^{A} + \ln Y_{jt}^{F} - \left(1-\sigma_{\rho}\right)\ln\Pi_{it} - \left(1-\sigma_{\rho}\right)\ln\mathrm{P}_{jt} + \zeta_{ij}\right\} + \epsilon_{ijt}, \qquad \text{[B3]}$$

where $a = -\ln X_{t}$, $\zeta_{ij} = \left(1-\sigma_{\rho}\right)\ln t_{ij}$, and ϵ_{ijt} is the stochastic term. Eq. B3 includes pairwise fixed effects ζ_{ij} which account for all time-invariant factors that vary at the exporter-importer level.

The exporter- and importer-size terms from Eq. B3 are parametrized as:

$$X_{it}^{A} = \exp\left\{\alpha_1 \ln D_{it}^{A} + \delta_1 \ln W_{it}^{A} + \lambda_{21}\ln G_{it}^{A} + \lambda_{22}\ln T_{it}^{A} + \lambda_{23}\ln R_{it}^{A} + \eta_{CZ_{i}t}\right\}, \qquad \text{[B4a]}$$

$$Y_{jt}^{F} = \exp\left\{\alpha_2 \ln D_{jt}^{A} + \delta_2 \ln W_{jt}^{A} + \lambda_{31}\ln G_{jt-1}^{F} + \lambda_{32}\ln T_{jt}^{A} + \lambda_{33}\ln R_{jt}^{A} + \lambda_{34}\ln P_{jt}^{A} + \theta_{CZ_{j}t}\right\}, \text{[B4b]}$$

where drought D_{it}^{A} and wetness W_{it}^{A} are the extreme weather variables; G_{it}^{A} is the production of agricultural commodities in state i representing the exporters' capacity to produce agricultural goods; T_{it}^{A} is the growing degree days (GDD) of the growing season, and R_{it}^{A} is the precipitation during the growing season. With $\eta_{CZ_{i}t}$ we capture time-variant factors that vary by climate-zone of exporting states, factors such as climate, soil conditions, and irrigation practices. The same corresponding variables are included for the importer j's size terms. Note that the importers' G_{jt-1}^{F} 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_{jt}^{A} is included to capture household demand. The climate-zone by year fixed effects of importing states are given as $\theta_{CZ_{j}t}$.

While the MRTs in Eq. B3, Π_{ikt} and P_{jkt}, are usually controlled for with exporter-time and importer-time fixed effects (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 extreme weather shocks. Instead, we approximate the MRTs by an option that follows Baier and Bergstrand (Baier and Bergstrand, 2009) and provides virtually identical coefficients without measurement errors:

$$(\sigma_{\rho}-1)\ln\Pi_{it}+(\sigma_{\rho}-1)\ln P_{jt}=\phi_{1}\mathrm{MRT}_{ijt}(\ln Dist_{ij})+\phi_{2}\mathrm{MRT}_{ijt}(C_{ij})+\phi_{3}\mathrm{MRT}_{ijt}(H_{ij}). \quad [B5]$$

Taking the log of distance as an example, $\mathrm{MRT}_{ijt}(\ln Dist_{ij})$ is approximated as $\sum_{k=1}^{N} m_{kt}\ln Dist_{kj}+\sum_{l=1}^{N} m_{lt}\ln Dist_{il}-\sum_{k=1}^{N}\sum_{l=1}^{N} m_{kt}m_{lt}\ln Dist_{kl}$ where $m_{kt}=X_{kt}/X_{t}$ is the exporter's production relative to total U.S. production, and $m_{lt}=Y_{lt}/Y_{t}$ 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.

Appendix C. Effect of extreme weather on food manufacturing

Eq. C1 is the full matrix derivative of manufactured food production with respect to changes in drought (our exogenous extreme weather shock).

$$\frac{\boldsymbol{\partial \ln Y}}{\boldsymbol{\partial \ln D_k}} = \begin{bmatrix} \frac{\partial \ln Y_1}{\partial \ln D_{1k}} & \cdots & \frac{\partial \ln Y_1}{\partial \ln D_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \ln Y_n}{\partial \ln D_{1k}} & \cdots & \frac{\partial \ln Y_n}{\partial \ln D_{nk}} \end{bmatrix}. \qquad [\text{C1}]$$

The diagonal elements are the *home-state effects* which are given as Eq. C2. The first term is the change in manufactured food production through changes in home-state produced input, I_{hk}, which we call the *home-state input channel*. The second term is the change that adjusts through changes of imported inputs, M_{jk}, which we refer to as the *imported input channel*.

$$\frac{\partial \ln Y_j}{\partial \ln D_{hk}} = \frac{\partial \ln Y_j}{\partial \ln I_{hk}} \frac{\partial \ln I_{hk}}{\partial \ln D_{hk}} + \frac{\partial \ln Y_j}{\partial \ln M_{jk}} \frac{\partial \ln M_{jk}}{\partial \ln D_{jk}}. \qquad [\text{C2}]$$

Next, we find the output elasticity, $\frac{\partial \ln Y}{\partial \ln I}$ and $\frac{\partial \ln Y}{\partial \ln M}$, given a nested CD production function with CES sub-aggregates of inputs. Assuming one input group for the production function equation Eq. 1 (in the main manuscript), the output elasticity of local input I on food production Y is Eq. C4:

$$Y_j = \left(PT_j\right) L_j^{(1-\beta-\gamma)} K_j^{\beta} \left\{ \left[I_h^{\frac{\sigma-1}{\sigma}} + M_j^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \right\}^{\gamma}, \qquad [C3]$$

$$\frac{d\ln Y_j}{d\ln I_h} = (1-\beta-\gamma)\cdot\frac{d\ln L_j}{d\ln I_h} + \beta\cdot\frac{d\ln K_j}{d\ln I_h} + \gamma\cdot\frac{I_h^{\frac{\sigma-1}{\sigma}}}{I_h^{\frac{\sigma-1}{\sigma}} + M_j^{\frac{\sigma-1}{\sigma}}} + \gamma\cdot\frac{M_j^{\frac{\sigma-1}{\sigma}}}{I_h^{\frac{\sigma-1}{\sigma}} + M_j^{\frac{\sigma-1}{\sigma}}}\cdot\frac{d\ln M_j}{d\ln I_h}, \qquad [C4]$$

where L is labor, K is capital, β is the output elasticity of capital, γ is the output elasticity of the input group, and σ is the elasticity of substitution. Eq. C4 is composed of direct effect and indirect effects that take place through adjustments of other aggregate inputs. We assume a setting where there are no adjustments between labor, capital in food manufacturing, and agricultural inputs ($\frac{d\ln L}{d\ln I} = 0$ and $\frac{d\ln K}{d\ln I} = 0$). Furthermore, given $\sigma = 1$, the inputs operate independently ($\frac{d\ln M}{d\ln I} = 0$) without any constraints. This results in the direct marginal effect of local (imported) inputs as $\frac{\gamma}{2}$ ($= \frac{d\ln Y}{d\ln I} = \frac{d\ln Y}{d\ln M}$). Thus, the home-state effect of drought in agricultural commodity k is given as Eq. C5 when we substitute the parameters from the gravity for the drought effects on trade from the origin state ($\frac{\partial\ln I_{hk}}{\partial\ln D_{hk}}$) and destination state ($\frac{\partial\ln M_{jk}}{\partial\ln D_{jk}}$):

$$\frac{\partial\ln Y_j}{\partial\ln D_{hk}} = \frac{\gamma_k}{2}\cdot\alpha_{1k} + \frac{\gamma_k}{2}\cdot\alpha_{3k}, \qquad [C5]$$

where α_{1k} is the home drought effect on local agricultural input, and α_{3k} is the effect of drought on imported inputs that is happening in other states of origin.

Next, we have the *inward effect* on the off-diagonal row elements of the derivative matrix C1. This is the change in local (destination) food production induced from an increase in drought taking place in other (commodity-producing) origin states. We decompose it further in Eq. C6.

$$\frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\partial \ln Y_j}{\partial \ln I_{hk}} \frac{\partial \ln I_{hk}}{\partial \ln D_{ik}} + \frac{\partial \ln Y_j}{\partial \ln M_{jk}} \frac{\partial \ln M_{jk}}{\partial \ln D_{ik}}. \qquad [C6]$$

The home-state channel of the inward effect ($\frac{\partial \ln Y}{\partial \ln I}\frac{\partial \ln I}{\partial \ln D}$) comes from the increase/decrease in agricultural inputs produced at home state induced by drought in other trading states. It can occur through changes in multilateral resistance components which in a conditional general equilibrium model is set to be determined exogenously. Therefore, we 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 given as Eq. C7 with our estimated parameters:

$$\frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_{2k} \cdot \frac{I_{ijk}}{M_{jk}}. \qquad [C7]$$

We can aggregate the inward effect, or the change in manufactured food production from national drought (or the row sum of the matrix exempt the local drought) as in Eq. C8:

$$\sum_{i}^{n} \frac{\partial \ln Y_j}{\partial \ln D_{ik}} = \frac{\gamma_k}{2} \cdot \alpha_{2k} \quad \forall\, i \neq j. \qquad [C8]$$

The *outward effect*, or the impact of a local drought on all other states of destination, is the same as Eq. C7 but with the i and j indices reversed. The aggregate outward effect is the column sum of the derivative matrix:

$$\sum_{i}^{n} \frac{\partial \ln Y_i}{\partial \ln D_{jk}} = \frac{\gamma_k}{2} \cdot \alpha_{2k} \sum_{i}^{n} \frac{I_{jik}}{M_{ik}} \quad \forall\, i \neq j. \qquad [C9]$$

Appendix D. Tables and figures

Table D1. Agricultural (SCTG 01–03) products used as inputs for manufactured food and beverages (SCTG 04–09).

SCTG										Sum (SCTG 04–09)		Household demand for SCTG 01–03	Export share of SCTG 01–03
Panel A. Input shares before rescaling (value of SCTG 01-03 per $1 output)													
	01	**02**	**03**	**04**	**05**	**06**	**07**	**08**	**09**				
01	0.109	0.002	0.003	0	0.574	0.007	0.193	0	0	0.767		0.056	0.001
02	0.082	0.031	0.004	0.137	0	0.355	0.052	0.035	0	0.579		0.019	0.174
03	0.005	0.004	0.059	0	0	0.022	0.315	0.014	0	0.337		0.262	0.203
Panel B. Rescaled input shares > 2% for SCTG 04-09													
01					0.749		0.251			1			
02				0.237		0.613	0.089	0.061		1			
03						0.066	0.934			1			

Note: Products are grouped as Standard Classification of Transported Goods (SCTG). Panel A shows the share of SCTG 01–03 inputs per dollar of production in SCTG 01–09, based on the national Input-Output table. The gray-shaded column shows the sum of SCTG 01–03 input shares that exceed 2% in SCTG 04–09. Panel B shows the rescaled shares of SCTG 01–03 used in SCTG 04–09. Authors' calculations based on the national Input-Output table (IMPLAN, 2020).

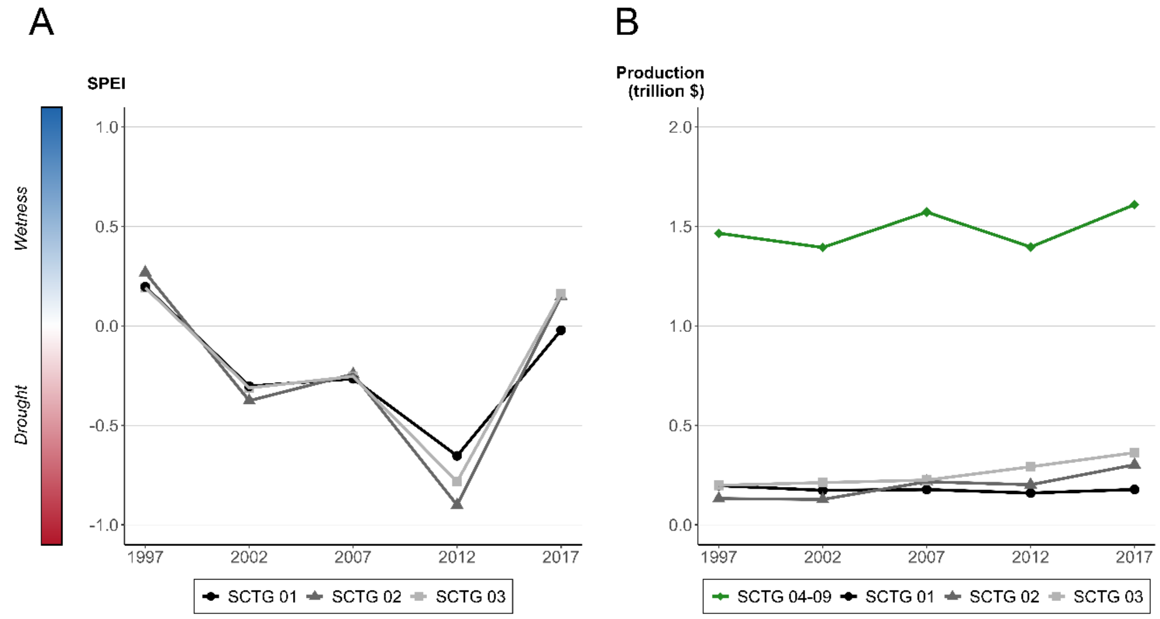

Fig. D1. SPEI and SCTG 01–09 production, 1997–2017.

Note: (A) The national average of the state-level SPEI across agricultural commodities in SCTG 01–03. Negative (or positive) SPEI indicates drought (or wetness). (B) The total production of manufactured food and beverages (SCTG 04–09), livestock and fish (SCTG 01), cereal grains (SCTG 02), and vegetables, fruits, and other crops (SCTG 03) is calculated as the sum of all the outflows—including intrastate and interstate—to U.S. states, measured in 2012 dollars.

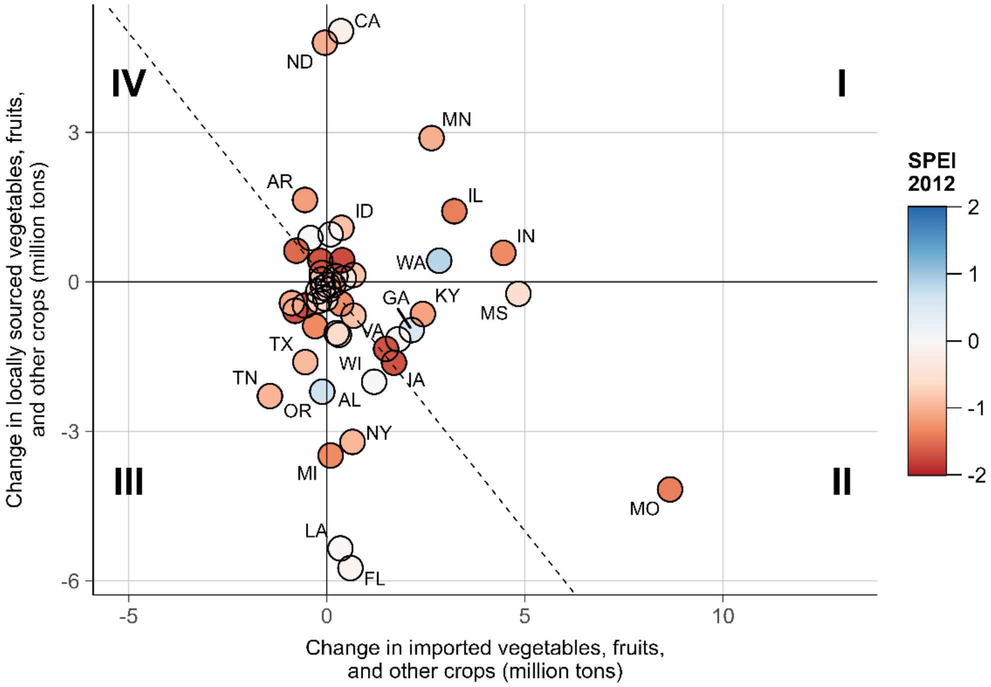

Fig. D2. **Scatter plot of the change in volume of locally sourced (y-axis) and imported (x-axis) vegetables, fruits, and other crops (SCTG 03) from 2007 to 2012.**

Note: Point colors represent the SPEI in 2012, with negative values (in red) indicating drought and positive values (in blue) indicating wetness. States above the $y = -x$ (dashed) line have a net increase in SCTG 03 compared to 2007, while those below it experienced a net decrease.

Table D2. Agriculture trade gravity results

	Animals and fish (SCTG 01)		Cereal grains (SCTG 02)		Vegetables, fruits, and other crops (SCTG 03)	
	(1)	(2)	(1)	(2)	(1)	(2)
Drought_home (*h*)	0.307 (0.306)		0.260 (0.179)		−0.127 (0.146)	
Drought_orig (*i*)	0.048 (0.533)		−0.531** (0.264)		−0.056 (0.320)	
Drought_dest (*j*)	−0.628 (0.510)		0.464* (0.289)		0.466 (0.302)	
Extreme drought_home (*h*)		0.241 (0.312)		0.225 (0.183)		−0.152 (0.143)
Mild drought_home (*h*)		0.319 (0.305)		0.241 (0.176)		−0.089 (0.150)
Extreme drought_orig (*i*)		−0.273 (0.536)		−0.753** (0.323)		−0.119 (0.317)
Mild drought_orig (*i*)		0.127 (0.545)		−0.454 (0.311)		−0.129 (0.331)
Extreme drought_dest (*j*)		−0.039 (0.568)		0.590* (0.346)		0.652** (0.301)
Mild drought_dest (*j*)		−0.700 (0.511)		0.494* (0.298)		0.343 (0.320)
Wetness_home (*h*)	0.047 (0.348)	0.049 (0.342)	−0.002 (0.141)	−0.001 (0.143)	0.127 (0.161)	0.152 (0.167)
Wetness_orig (*i*)	−0.107 (0.626)	−0.182 (0.650)	0.407 (0.458)	0.465 (0.466)	−0.331 (0.262)	−0.365 (0.268)
Wetness_dest (*j*)	1.792** (0.707)	1.720** (0.725)	0.197 (0.317)	0.219 (0.292)	0.351 (0.248)	0.260 (0.237)
Ag production_orig (*i*)	0.747*** (0.115)	0.746*** (0.115)	0.592*** (0.086)	0.590*** (0.086)	0.448*** (0.068)	0.448*** (0.068)
Food production_dest (*j*)	−0.161 (0.178)	−0.163 (0.178)	−0.059 (0.181)	−0.055 (0.184)	0.063 (0.150)	0.059 (0.153)
GDD_home (*h*)	0.110 (0.893)	0.130 (0.929)	0.216 (0.885)	0.217 (0.898)	0.262 (0.674)	0.241 (0.675)
GDD_orig (*i*)	−1.366 (1.658)	−1.149 (1.682)	0.302 (1.545)	0.202 (1.532)	−0.308 (1.417)	−0.301 (1.406)
GDD_dest (*j*)	6.701*** (1.658)	6.328*** (1.676)	−1.986* (1.168)	−1.908* (1.151)	0.193 (1.642)	0.324 (1.650)
Precipitation_home (*h*)	0.052 (0.389)	0.074 (0.380)	0.385 (0.255)	0.370 (0.255)	−0.111 (0.135)	−0.119 (0.133)
Precipitation_orig (*i*)	0.072 (0.713)	0.222 (0.707)	−0.434 (0.407)	−0.482 (0.402)	0.106 (0.235)	0.103 (0.239)
Precipitation_dest (*j*)	−0.802 (0.648)	−0.807 (0.660)	−0.060 (0.392)	−0.036 (0.375)	0.203 (0.247)	0.241 (0.240)
Population_dest (*j*)	−1.631* (0.958)	−1.657* (0.974)	1.116 (0.815)	1.130 (0.826)	0.548 (0.577)	0.529 (0.577)
MRTs	Y	Y	Y	Y	Y	Y
State-pair F.E.	Y	Y	Y	Y	Y	Y
Exporter climate zone-year F.E.	Y	Y	Y	Y	Y	Y

Importer climate zone-year F.E.	Y	Y	Y	Y	Y	Y
R-squared*	0.969	0.969	0.977	0.978	0.984	0.984
Pseudo R-squared	0.963	0.963	0.965	0.965	0.973	0.973
N	5,680	5,680	7,555	7,555	10,940	10,940

Note: The dependent variable is export volume of each agricultural SCTG. Each column reports regression results of the gravity model equation using (1) drought, and (2) extreme/mild drought. All models include fixed effects for state pairs, exporter climate-zone-by-year and importer climate-zone-by-year effects, and multilateral resistance terms (MRTs for distance, neighbor, and home). GDD is growing degree days. R-squared* is the squared correlation between observed and predicted values, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered by state pairs.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D3. First-stage results

Observed agricultural inputs	Animals and fish (SCTG 01)		Cereal grains (SCTG 02)		Vegetables, fruits, and other crops (SCTG 03)	
	Drought	Ext./mild drought	Drought	Ext./mild drought	Drought	Ext./mild drought
	(1)	(2)	(1)	(2)	(1)	(2)
Predicted agricultural inputs (instruments)						
SCTG 01	1.168***	1.158***	0.056	0.055	−0.033	−0.035
	(0.119)	(0.116)	(0.099)	(0.098)	(0.075)	(0.076)
SCTG 02	−0.344	−0.353	0.878***	0.872***	0.065	0.060
	(0.329)	(0.332)	(0.109)	(0.108)	(0.071)	(0.070)
SCTG 03	0.094	0.133	0.354	0.373	0.946***	0.954***
	(0.207)	(0.208)	(0.245)	(0.249)	(0.124)	(0.123)
Capital	−0.163	−0.171	0.214	0.209	−0.038	−0.039
	(0.792)	(0.791)	(0.692)	(0.690)	(0.376)	(0.368)
State F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
SW *F*-statistics	124.61	120.77	44.52	43.77	71.41	70.34
Reduced-form *F*-statistics	40.36	41.57	28.82	28.51	21.08	21.77
N	240	240	240	240	240	240

Note: The dependent variable is observed agricultural input flows (SCTG 01–03), treated as endogenous and instrumented using predicted trade values from gravity model estimates (SCTG 01–03). Columns 1 uses drought; and columns 2 includes extreme/mild drought. Labor is excluded as all variables from second-stage production function are normalized by labor to impose constant returns to scale. Sander and Windmeijer (SW) *F*-statistics are reported as tests for weak instruments with multiple endogenous regressors. Reduced-form *F*-statistics indicate the joint significance of excluded instruments. All *F*-statistics exceed the standard threshold of 10. Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D4. Second-stage production function results

	Drought (1)	Ext./mild drought (2)
Animals and fish (SCTG 01)	–0.007	–0.007
	(0.013)	(0.012)
Cereal grains (SCTG 02)	0.060*	0.061*
	(0.032)	(0.032)
Vegetables, fruits, and other (SCTG 03)	0.035	0.036
	(0.062)	(0.064)
Capital	0.183*	0.183*
	(0.107)	(0.108)
Labor	0.640***	0.638***
	(0.155)	(0.156)
State F.E.	Y	Y
Year F.E.	Y	Y
R-squared*	0.681	0.680
N	240	240

Note: The dependent variable is the output of food and beverage manufacturing in 2012 dollars. Column 1 presents results using instruments based on drought, while column 2 uses instruments distinguishing extreme and mild drought. All estimations include two-way fixed effects (F.E.). R-squared* is the squared coefficient of correlation between the observed and predicted dependent variables, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

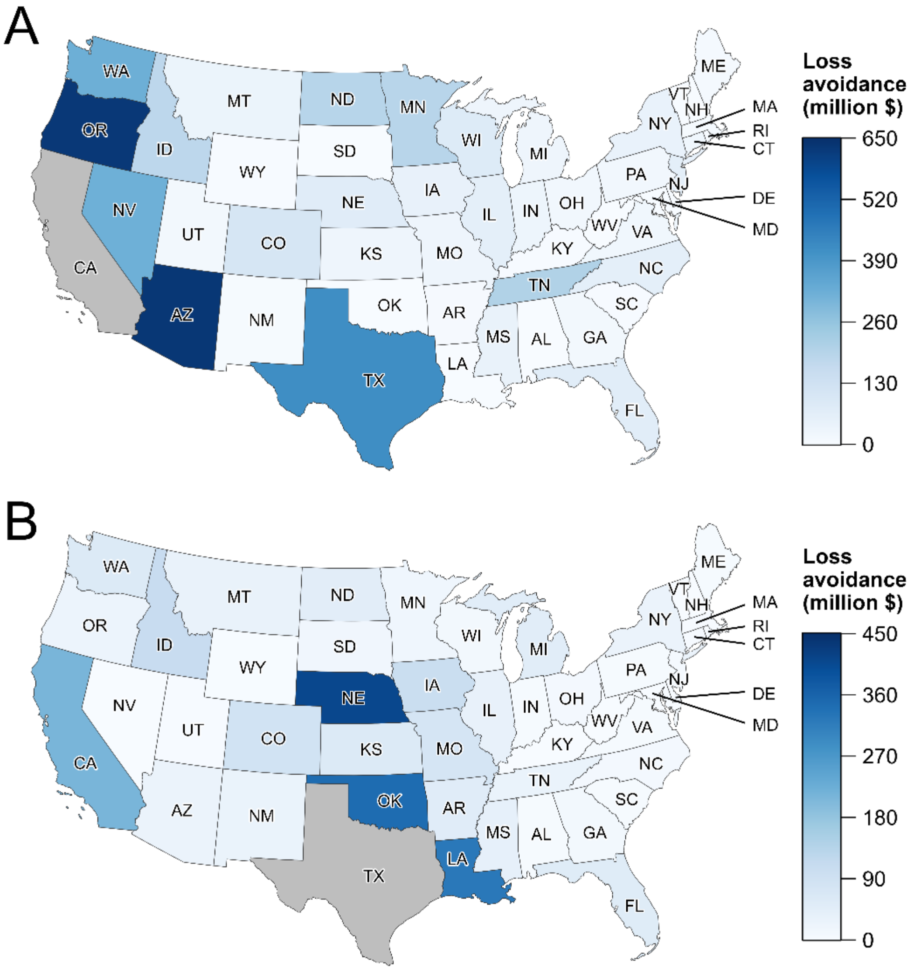

Fig. D3. Loss avoidance in food manufacturing in California (A) and Texas (B) following a 100% drought increase in local areas producing vegetables, fruits, and other crops, SCTG 03 (gray).

Note: The color code corresponds to the production losses California (or Texas) avoided by increasing SCTG 03 imports from origin states. The darker the color, the higher the avoided loss.

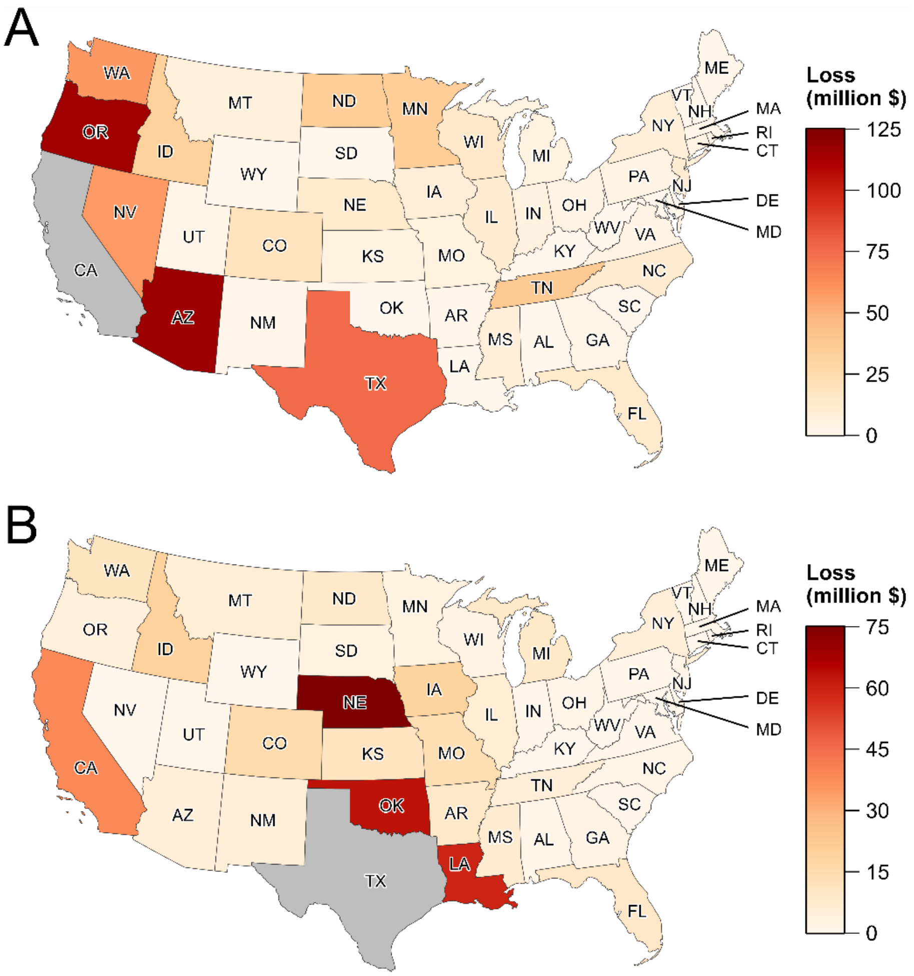

Fig. D4. Loss in food manufacturing in California (A) and Texas (B) following a 100% drought increase in the areas of the state of origin producing vegetable, fruit, and other crop, SCTG 03 (colored).

Note: The color code corresponds to the extent to which food manufacturing production in California (or Texas) decreases following a drought in each of the colored states, from which it imports SCTG 03 commodities.

Fig. D5. Loss in food manufacturing in the state of destination (colored) following a 100% drought increase on the cereal grain (SCTG 02) producing areas of California (A) and Texas (B).

Note: The color code corresponds to the extent to which food manufacturing production in the colored states decreases following a drought in California (or Texas), from which they import SCTG 02 commodities.

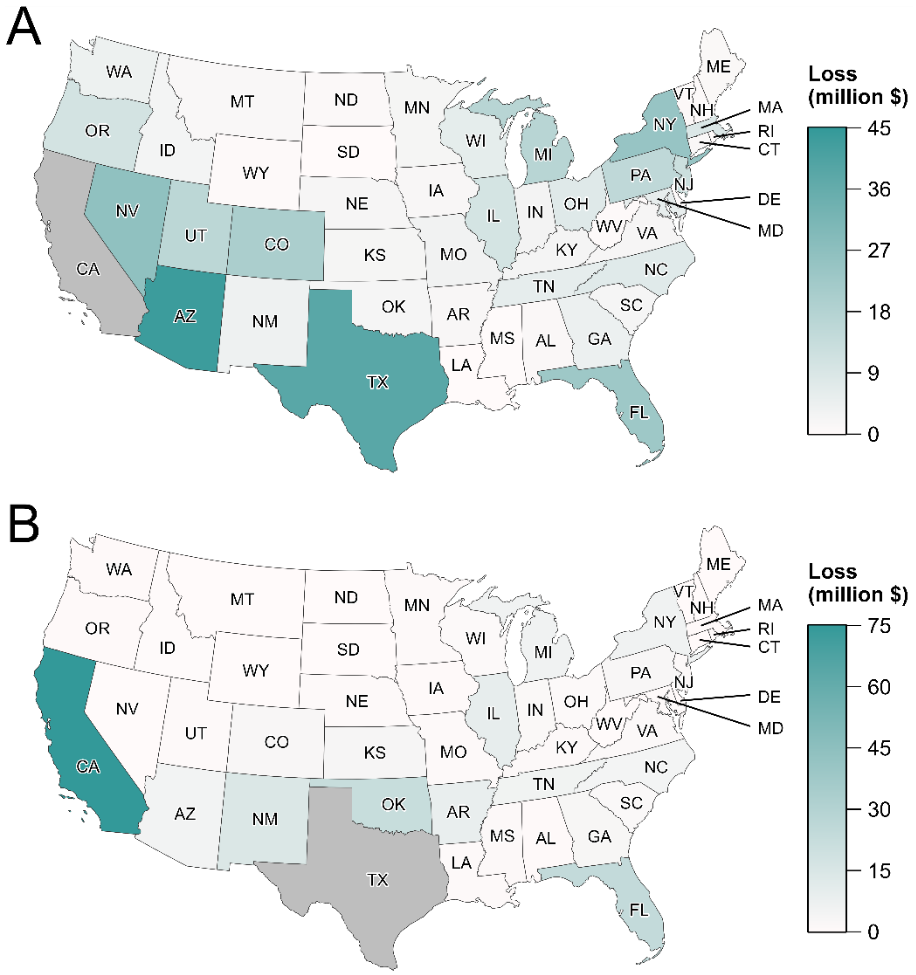

Fig. D6. Loss in food manufacturing in the state of destination (colored) following a 100% drought increase in the areas of California (A) and Texas (B) producing vegetable, fruit, and other crops (SCTG 03).

Note: The color code corresponds to the extent to which food manufacturing production in the colored states decreases following a drought in California (or Texas), from which they import SCTG 03 commodities.

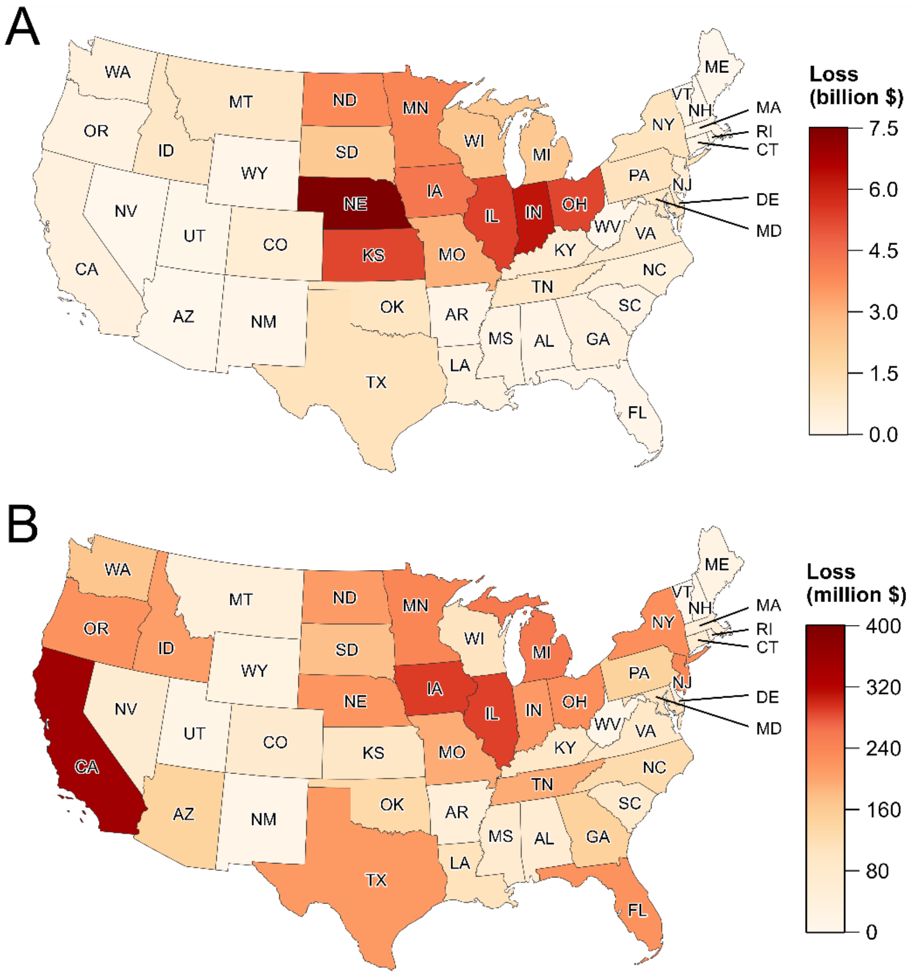

Fig. D7. Loss in national food manufacturing following a 100% drought increase in the areas of the origin state (colored) producing SCTG 02 (A) and SCTG 03 (B) commodities.

Note: National food production loss coming from a drought in the areas producing SCTG 02 (cereal grains) and SCTG 03 (vegetables, fruits, and other crops) in each of the colored states. Colors represent losses in nationwide food production levels.

Table D5. Data preprocessing steps and source—gravity model

Data type	Source	Original unit	Aggregate unit	Preprocessing steps
Trade data (SCTG 01–03)	Freight Analysis Framework	State-to-state-level (annual)	State-to-state-level (annual)	Excluded flows related to international imports and exports to focus solely on domestic trade; included intrastate flows to allow analysis of local versus imported input substitution; included traded commodities by all modes of transportation; adjusted all monetary values to 2012 USD using producer price indices; data compiled quinquennially from 1997 to 2017 across 48 states and 3 commodity groups, resulting in 34,560 data points
Weather (SPEI, GDD, Precipitation)	ERA5-Land database; United States Department of Agriculture (USDA)	County-level (daily/ monthly)	State-level (annual)	Generated monthly county-level SPEI and daily county-level GDD and precipitation using reanalysis data; used spatial weights based on farmland acreage (SCTG 02 & 03) or livestock sales (SCTG 01) standardized SPEI values computed as deviations from 1950–2014 historical baseline; growing season periods for SCTG 02 and 03 commodities were determined using USDA planting and harvesting dates, with state-level spatial weights derived from farmland acreage; SPEI values for SCTG 01 used full-year averages; aggregated to annual, state-level values using spatial and temporal weighting, yielding crop- and region-specific climate indicators.
Agricultural production; Importer demand (intermediate, household	Freight Analysis Framework (FAF); Bureau of Economic Analysis USDA; U.S. Census	State-level (annual)	State-level (annual)	Agricultural production capacity is measured by the sum of FAF trade outflows (interstate + intrastate) per state and commodity; importer demand is proxied by one-year lagged value-added of food and beverage manufacturing, weighted by commodity-specific input shares from the Input-Output matrix—specifically, the sum of SCTG 01-03 shares above 2% used in food and beverage manufacturing (SCTG 04-07); household demand is captured using population by state;
Distance; MRTs	Open Source Routing Machine (OSRM); Commodity Flow Survey (CFS)	City-level (most populated city per state)	State-pair level	Calculated shortest truck travel time between largest cities in each state using OSRM; used average within-state shipment distances from the CFS for intrastate flows; approximated multilateral resistance terms (MRTs) for distance, contiguity, and home-state bias using agricultural production and importer demand share-based indices; avoided geometric distance issues common in domestic models; consistent with truck-dominated freight transportation in the FAF dataset.
Climate zone fixed effects	National Oceanic and Atmospheric Administration (NOAA)	Climate zones (NOAA-defined)	Climate zone-level (annual)	Assigned each state to one of 9 NOAA-defined climate zones; applied zone-by-year fixed effects to control for unobserved, time-varying zone-specific conditions like soil and irrigation. 9 zones: - Northwest: Washington, Idaho, Oregon - West: California, Nevada - Southwest: Utah, Colorado, Arizona, New Mexico - Northern Rockies and Plains (West North Central): Montana, North Dakota, Wyoming, South Dakota, Nebraska - South: Kansas, Oklahoma, Texas, Arkansas, Louisiana, Mississippi - Upper Midwest (East North Central): Minnesota, Wisconsin, Michigan, Iowa - Ohio Valley (Central): Missouri, Illinois, Indiana, Ohio, West Verginia, Kentucky, Tennessee

				- Southeast: Alabama, Georgia, South Carolina, North Carolina, Florida, Virginia - Northeast: Pennsylvania, Maryland, Delaware, New Jersey, Connecticut, Rhode Island, Massachusetts, Vermont, New York, New Hampshire, Memphis
International imports and exports (robustness check only)	Freight Analysis Framework	State-level (annual)	State-level (annual)	International imports are assigned to the U.S. state where the foreign commodities are ultimately consumed or used—not where they first enter the country; exports are assigned to the state where the goods begin their domestic transport to a foreign destination—not the port of exit; adjusted all monetary values to 2012 USD using producer price indices; data compiled quinquennially from 1997 to 2017 across 48 states and 3 commodity groups.

Table D6. Data preprocessing steps and source—food manufacturing production function

Data type	Source	Original unit	Aggregate unit	Preprocessing steps
Food manufacturing output	Freight Analysis Framework (FAF); SIC to NAICS concordance	State-level (annual)	State-level (annual)	Measured by the sum of FAF trade outflows (interstate + intrastate) per state; included flows for food manufacturing commodities including beverage and tobacco manufacturing (SCTG 04–09); robustness check for food and beverage manufacturing only (SCTG 04–07); excluded flows related to international imports and exports to focus solely on domestic trade; adjusted all monetary values to 2012 USD using producer price indices; data compiled quinquennially from 1997 to 2017 across 48 states.
Labor in manufacturing	Bureau of Economic Analysis; U.S. Census Bureau SIC-NAICS concordance	Region-level (e.g., Plains, New England) or SIC-state	State-level (annual)	Constructed state-level labor data for food, beverage, and tobacco manufacturing; for missing values, imputed using historical ratios of state-to-region employment, assuming temporal stability; in 1997, converted SIC-based employment counts to NAICS using concordance tables and allocation percentages; missing values for specific industries (e.g., tobacco in Delaware) filled with averaged estimates from adjacent years; ensured consistent mapping of employment across classification systems for long-term comparability.
Capital in manufacturing	Federal Reserve Board (FRB); BEA	National-level (annual)	State-level (annual)	Allocated national capital stock (from the FRB, NAICS 311 and 312, in 2012 USD) across states and years in proportion to BEA value-added for NAICS 311-312.
Locally-grown agricultural inputs	FAF	Observed value at state-to-state level (annual)	State-level (annual)	Intrastate flows instrumented with gravity-model-based estimates of intrastate flows.
Agricultural inputs imported from other states	FAF	Observed value at state-to-state level (annual)	State-level (annual)	Summed import flows instrumented with gravity-predicted imports, summed over exporting states (excluding intrastate flows).
International imports (robustness check only)	FAF	State-level (annual)	State-level (annual)	International imports are assigned to the U.S. state where the foreign commodities are ultimately consumed or used—not where they first enter the country; adjusted all monetary values to 2012 USD using producer price indices; data compiled quinquennially from 1997 to 2017 across 48 states and 3 commodity groups.

Table D7. Reduced-form estimates of food output on covariates used to construct instruments

	Coefficient
Population_dest (*j*)	–0.459 (0.384)
Food production_dest (*j*)	0.106 (0.088)
State F.E.	Y
Year F.E.	Y
N	240

Note: The dependent variable is food and beverage manufacturing output, regressed on state *j*'s covariates used to construct gravity-based instruments for agricultural inputs. The estimation includes two-way fixed effects (F.E.). Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D8. Estimates and standard errors for Fig. 4

	Destination			
	California		Texas	
Origin	Estimated value	Std. err.	Estimated value	Std. err.
Alabama	0.00	0.00	0.07	0.04
Arizona	8.51	4.48	4.52	2.38
Arkansas	12.83	6.76	22.62	11.92
California			33.89	17.86
Colorado	67.76	35.72	42.00	22.14
Connecticut	0.01	0.01	2.91	1.53
Delaware	0.00	0.00	0.00	0.00
Florida	0.14	0.07	25.84	13.62
Georgia	0.13	0.07	0.03	0.02
Idaho	124.09	65.41	1.09	0.57
Illinois	126.24	66.55	107.70	56.77
Indiana	3.41	1.80	4.88	2.57
Iowa	1,387.11	731.20	44.30	23.35
Kansas	63.76	33.61	1,783.92	940.37
Kentucky	0.80	0.42	0.30	0.16
Louisiana	1.67	0.88	81.38	42.90
Maine	0.00	0.00	0.00	0.00
Maryland	0.00	0.00	0.00	0.00
Massachusetts	0.27	0.14	0.02	0.01
Michigan	4.58	2.41	1.26	0.66
Minnesota	365.37	192.60	78.58	41.42
Mississippi	0.00	0.00	0.35	0.18
Missouri	365.37	192.60	409.41	215.81
Montana	76.90	40.54	0.02	0.01
Nebraska	2,829.97	1,491.78	330.68	174.31
Nevada	0.76	0.40	0.00	0.00
New Hampshire	0.00	0.00	0.00	0.00
New Jersey	0.01	0.00	0.00	0.00
New Mexico	0.05	0.02	49.88	26.29
New York	3.03	1.60	0.60	0.32
North Carolina	0.10	0.05	0.02	0.01
North Dakota	287.09	151.34	64.43	33.96
Ohio	25.63	13.51	34.23	18.04
Oklahoma	14.63	7.71	327.66	172.72
Oregon	106.06	55.91	9.91	5.22
Pennsylvania	0.10	0.05	0.38	0.20
Rhode Island	0.00	0.00	0.00	0.00
South Carolina	0.00	0.00	0.00	0.00
South Dakota	145.84	76.88	41.79	22.03
Tennessee	0.22	0.12	0.01	0.01
Texas	146.19	77.06		
Utah	4.82	2.54	0.09	0.05
Vermont	0.00	0.00	0.00	0.00
Virginia	1.26	0.66	0.04	0.02
Washington	1.00	0.52	0.00	0.00
West Virginia	0.00	0.00	0.00	0.00
Wisconsin	0.00	0.00	52.44	27.64
Wyoming	0.01	0.00	0.00	0.00

Note: Values are in million U.S. dollars. The top 5 values are highlighted.

Table D9. Estimates and standard errors for Fig. 6

	Destination			
	California		Texas	
Origin	Estimated value	Std. err.	Estimated value	Std. err.
Alabama	0.00	0.00	–0.09	0.05
Arizona	–10.87	5.73	–5.77	3.04
Arkansas	–16.39	8.64	–28.89	15.23
California			–43.29	22.82
Colorado	–86.56	45.63	–53.65	28.28
Connecticut	–0.01	0.01	–3.72	1.96
Delaware	0.00	0.00	0.00	0.00
Florida	–0.17	0.09	–33.01	17.40
Georgia	–0.16	0.09	–0.04	0.02
Idaho	–158.52	83.56	–1.39	0.73
Illinois	–161.27	85.01	–137.58	72.52
Indiana	–4.36	2.30	–6.23	3.28
Iowa	–1,771.95	934.06	–56.59	29.83
Kansas	–81.45	42.93	–2,278.84	1,201.26
Kentucky	–1.03	0.54	–0.38	0.20
Louisiana	–2.14	1.13	–103.96	54.80
Maine	0.00	0.00	0.00	0.00
Maryland	0.00	0.00	0.00	0.00
Massachusetts	–0.34	0.18	–0.02	0.01
Michigan	–5.85	3.08	–1.61	0.85
Minnesota	–466.74	246.04	–100.38	52.91
Mississippi	0.00	0.00	–0.44	0.23
Missouri	–466.74	246.04	–522.99	275.69
Montana	–98.24	51.78	-0.02	0.01
Nebraska	–3,615.10	1,905.65	–422.42	222.67
Nevada	–0.98	0.51	0.00	0.00
New Hampshire	0.00	0.00	0.00	0.00
New Jersey	–0.01	0.00	0.00	0.00
New Mexico	–0.06	0.03	–63.72	33.59
New York	–3.88	2.04	–0.76	0.40
North Carolina	–0.13	0.07	–0.02	0.01
North Dakota	–366.75	193.32	–82.31	43.39
Ohio	–32.74	17.26	–43.73	23.05
Oklahoma	–18.69	9.85	–418.57	220.64
Oregon	–135.49	71.42	–12.66	6.67
Pennsylvania	–0.12	0.07	–0.48	0.25
Rhode Island	0.00	0.00	0.00	0.00
South Carolina	0.00	0.00	0.00	0.00
South Dakota	–186.30	98.21	–53.39	28.14
Tennessee	–0.28	0.15	–0.01	0.01
Texas	–186.75	98.44		
Utah	–6.16	3.25	–0.11	0.06
Vermont	0.00	0.00	0.00	0.00
Virginia	–1.61	0.85	–0.05	0.03
Washington	–1.27	0.67	0.00	0.00
West Virginia	0.00	0.00	0.00	0.00
Wisconsin	0.00	0.00	–66.99	35.31
Wyoming	–0.01	0.00	0.00	0.00

Note: Values are in million U.S. dollars. The top 5 values are highlighted.

Appendix E. Robustness checks—agriculture trade gravity

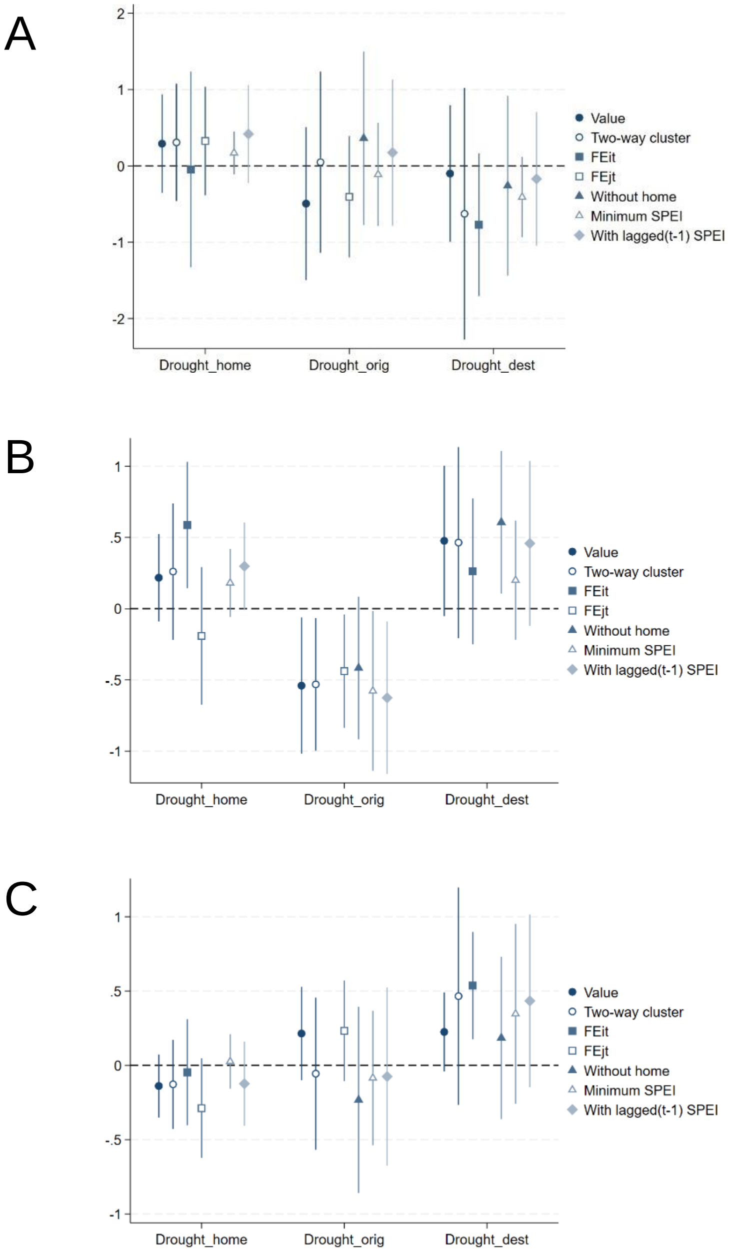

Fig. E1. Effect of drought on agriculture trade.

Note: The graph shows the 95% confidence interval (CI) of the estimates for three drought variables across (A) animals and fish (SCTG 01), (B) cereal grains (SCTG 02), and (C) vegetables, fruits, and other agricultural products (SCTG 03). The first lines are the estimates when the dependent variable is measured in monetary values (2012 U.S. dollars). The second lines are the estimates when the standard errors are two-way clustered by destination and origin. The third lines are the estimates with exporter-importer and exporter-by-year fixed effects. The fourth estimates include importer-by-year fixed effects. Next, we report the estimates without the home-drought variable. The estimates using the minimum monthly SPEIs (as opposed to the average) are also shown. The last vertical lines display the CIs for contemporaneous drought when including lagged drought variables.

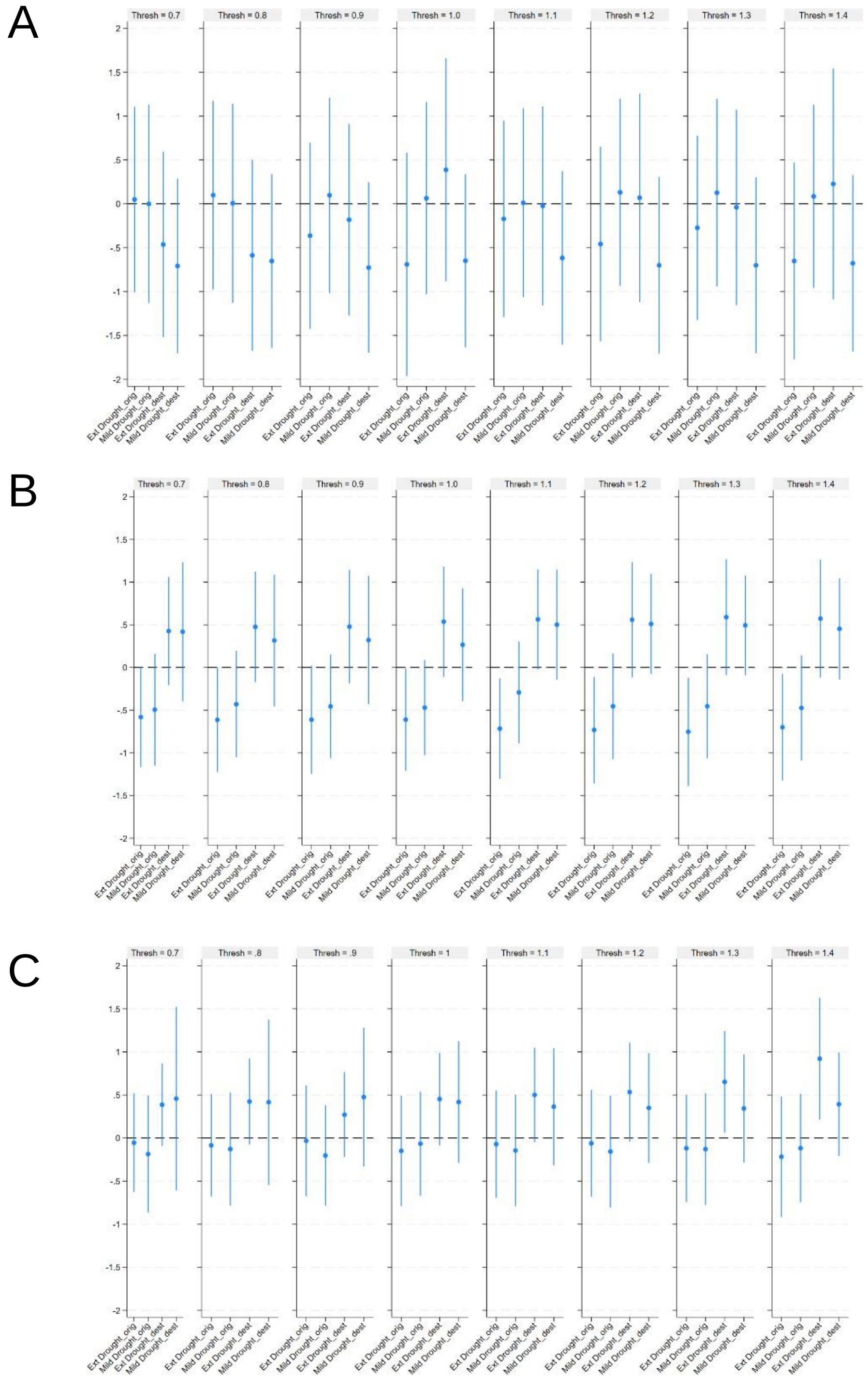

Fig. E2. Effect of extreme/mild drought on agriculture trade with varying thresholds.

Note: Each panel shows the point estimate and associated 95% confidence intervals of the impact of extreme/mild drought in the importing and exporting states with different thresholds for (A) animals and fish (SCTG 01), (B) cereal grains (SCTG 02), and (C) vegetables, fruits, and other agricultural products (SCTG 03).

Appendix F. Robustness checks—IV approach

We conduct several robustness checks of the instrumental variable (IV) estimation approach. First, we construct a variant of the gravity-based instruments which limits the covariates to those that are strictly exogenous. They are the exporters' agricultural production, weather conditions, and bilateral trade costs. In the same spirit as Felbermayr and Gröschl (Felbermayr and Gröschl, 2013), the instruments are constructed by excluding the importers' food production (as intermediate demand for agricultural inputs), population (as final household demand), and the MRTs. We refer to this approach as the model à la Felbermayr and Gröschl (F&G for short). Table F1 reports the gravity results using drought without threshold (columns 1) and with extreme/mild drought (columns 2). The coefficient estimates for extreme drought reinforce the findings from the full specification: extreme drought reduces grain exports to unaffected states while increasing exports to states experiencing it.

Second, we construct an international variant of the gravity-based instruments which includes for each state the role of foreign exports and imports in the gravity and the role of foreign imports in the second-stage regression (food manufacturing production function) as a robustness check. These are control variables that capture the role of foreign markets and, by extension, all the factors that drive international trade, including distance, production, demand and drought/wetness in foreign regions. Given that the FAF data do not specify the foreign countries with which each U.S. state trades agricultural commodities, we believe our approach to be a reasonable solution. The full gravity model estimates are in Table F2 for drought without thresholds (columns 1) and with extreme/mild drought (columns 2). We refer to this as the international model. We find that, even after controlling for foreign trade, domestic flows of grains (SCTG 02) and other crops (SCTG 03) remain highly responsive to drought conditions in both exporting and importing states—with particularly stronger effects under extreme drought.

Third, we perform a robustness check by including importer-level food production and population as additional controls in the second-stage regression. While the same gravity-based instruments from our main specification are used, we introduce these controls to account for potential confounding factors—specifically, components of food output in the importing state that may not be explained solely by changes in traded agricultural inputs. This helps isolate the effect of trade-related input shocks from other channels through which the instrument covariates might influence food production.

Fourth, we conduct a robustness check using food sector capital and labor as proxies for input demand in destination states, hence replacing lagged food production in the gravity model. Instruments are constructed from a full gravity model with exporter and importer characteristics by substituting demand with food sector capital and labor, both of them being also used as covariates in the second stage. The gravity model results in Table F3 consistently show that droughts in destination states increase agricultural imports, while droughts in origin states reduce exports. Both first- and second-stage estimates remain robust.

Finally, we use an alternative definition of food output that includes food manufacturing products but excludes tobacco. This specification focuses on SCTG groups 04–07. The construction of food production follows the same method as in the main output definition (SCTG 04–09): it is the total outflow of SCTG 04–07 commodities to all states, including intrastate flows. Labor for SCTG 04–07 is constructed as described in *SI Appendix A3*. To impute the 1997 value, we apply the average share of food manufacturing in total food, beverage, and tobacco manufacturing—calculated from 1998 to 2017—to the corresponding 1997 total. Capital for SCTG 04–07 is constructed following the approach outlined in *Materials and Methods* of the main manuscript: national capital data from the Federal Reserve Board is disaggregated to the state level based on the value-added of food manufacturing products in each state. We refer to this as the SCTG 04–07 model.

The same IV approach described in *Materials and Methods* is applied here. Table F4 presents the first-stage regression results using gravity-based instruments constructed from drought exposure without thresholds. The table reports results for four specifications: (1) the model à la F&G, (2) the international model, (3) the model conditional on intermediate and household food demand, (4) the specification using food sector capital and labor as proxies for input demand in gravity, and (5) the SCTG 04–07 output. Each panel reports the correlation between observed and predicted trade flows for three commodity groups: animals and fish (A), cereal grains (B), and vegetables, fish, and other crops (C). Table F5 presents the corresponding second-stage results, maintaining the same columns and using gravity instruments based on drought without thresholds.

Tables F6 and F7 report the first- and second-stage results, respectively, using gravity-based instruments constructed from extreme and mild drought observations. Both tables follow the same structure as Tables F4 and F5.

Overall, the exercises yield results that are consistent with our main IV specification. First, the gravity-based instruments significantly predict observed (endogenous) flows of SCTG-classified agricultural commodities. Second, and more importantly, the second-stage estimates reinforce our core finding: U.S. food manufacturing remains responsive to disruptions in domestic grain supply, even under a range of alternative specifications. Notably, this relationship does not hold for imported agricultural inputs. While domestically sourced cereal grains exhibit a statistically significant effect on food manufacturing output, imported grains do not, suggesting that domestic inputs play a more critical role in sustaining

U.S. food production.

Table F1. Agriculture trade gravity results—model à la F&G

	Animals and fish (SCTG 01)		Cereal grains (SCTG 02)		Vegetables, fruits, and other crops (SCTG 03)	
	(1)	(2)	(1)	(2)	(1)	(2)
Drought_home (*h*)	0.243		0.233		–0.088	
	(0.362)		(0.153)		(0.173)	
Drought_orig (*i*)	–0.102		–0.516**		–0.031	
	(0.532)		(0.252)		(0.325)	
Drought_dest (*j*)	–0.555		0.424		0.466	
	(0.500)		(0.291)		(0.301)	
Extreme drought_home (*h*)		0.465		0.152		–0.192
		(0.418)		(0.152)		(0.155)
Mild drought_home (*h*)		0.256		0.237		–0.028
		(0.365)		(0.158)		(0.181)
Extreme drought_orig (*i*)		–0.230		–0.752**		–0.119
		(0.536)		(0.330)		(0.320)
Mild drought_orig (*i*)		–0.034		–0.439		–0.103
		(0.542)		(0.296)		(0.335)
Extreme drought_dest (*j*)		0.133		0.526		0.612**
		(0.563)		(0.351)		(0.298)
Mild drought_dest (*j*)		–0.614		0.453		0.346
		(0.502)		(0.301)		(0.321)
Wetness_home (*h*)	–0.030	–0.080	–0.115	–0.103	0.072	0.137
	(0.443)	(0.448)	(0.138)	(0.142)	(0.200)	(0.212)
Wetness_orig (*i*)	–0.085	–0.182	0.452	0.510	–0.330	–0.353
	(0.615)	(0.639)	(0.478)	(0.487)	(0.256)	(0.262)
Wetness_dest (*j*)	1.463**	1.366**	0.048	0.069	0.284	0.208
	(0.672)	(0.690)	(0.333)	(0.308)	(0.240)	(0.229)
Ag production_orig (*i*)	0.965***	0.962***	0.690***	0.686***	0.514***	0.508***
	(0.073)	(0.073)	(0.079)	(0.078)	(0.078)	(0.077)
GDD_home (*h*)	0.090	–0.002	0.234	0.203	0.244	0.196
	(1.016)	(1.056)	(0.880)	(0.889)	(0.682)	(0.678)
GDD_orig (*i*)	–1.603	–1.463	0.172	0.075	–0.198	–0.205
	(1.730)	(1.753)	(1.549)	(1.539)	(1.399)	(1.392)
GDD_dest (*j*)	6.714***	6.309***	–1.756	–1.700	0.188	0.324
	(1.802)	(1.825)	(1.188)	(1.174)	(1.594)	(1.607)
Precipitation_home (*h*)	0.056	0.110	0.326	0.301	–0.086	–0.115
	(0.427)	(0.432)	(0.215)	(0.214)	(0.149)	(0.143)
Precipitation_orig (*i*)	–0.099	0.036	–0.459	–0.506	0.145	0.130
	(0.714)	(0.708)	(0.401)	(0.398)	(0.233)	(0.237)
Precipitation_dest (*j*)	–0.669	–0.629	–0.040	–0.023	0.204	0.234
	(0.654)	(0.667)	(0.400)	(0.384)	(0.254)	(0.246)
MRTs	N	N	N	N	N	N
State-pair F.E.	Y	Y	Y	Y	Y	Y
Exporter climate zone-year F.E.	Y	Y	Y	Y	Y	Y

Importer climate zone-year F.E.	Y	Y	Y	Y	Y	Y
R-squared*	0.960	0.960	0.976	0.976	0.980	0.981
Pseudo R-squared	0.961	0.962	0.965	0.965	0.972	0.972
N	5,680	5,680	7,555	7,555	10,940	10,940

Note: The dependent variable is export volume of each agricultural SCTG. Each column reports regression results of the gravity equation using (1) drought, and (2) extreme/mild drought. All models include fixed effects for state pairs, exporter climate-zone-by-year and importer climate-zone-by-year effects. GDD is growing degree days. R-squared* is the squared correlation between observed and predicted values, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered by state pairs.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F2. Agriculture trade gravity results—including foreign SCTG 01–03 exports and imports

	Animals and fish (SCTG 01)		Cereal grains (SCTG 02)		Vegetables, fruits, and other crops (SCTG 03)	
	(1)	(2)	(1)	(2)	(1)	(2)
Drought_home (*h*)	0.295		0.277		–0.143	
	(0.313)		(0.173)		(0.143)	
Drought_orig (*i*)	0.030		–0.517*		–0.069	
	(0.528)		(0.266)		(0.318)	
Drought_dest (*j*)	–0.597		0.472		0.457	
	(0.503)		(0.291)		(0.298)	
Extreme drought_home (*h*)		0.207		0.216		–0.200
		(0.319)		(0.175)		(0.145)
Mild drought_home (*h*)		0.304		0.264		–0.098
		(0.311)		(0.171)		(0.146)
Extreme drought_orig (*i*)		–0.279		–0.765**		–0.141
		(0.532)		(0.322)		(0.314)
Mild drought_orig (*i*)		0.103		–0.435		–0.140
		(0.541)		(0.313)		(0.328)
Extreme drought_dest (*j*)		–0.017		0.597*		0.621**
		(0.559)		(0.347)		(0.295)
Mild drought_dest (*j*)		–0.668		0.506*		0.338
		(0.504)		(0.301)		(0.316)
Wetness_home (*h*)	0.053	0.060	0.010	0.016	0.164	0.199
	(0.344)	(0.336)	(0.142)	(0.147)	(0.156)	(0.164)
Wetness_orig (*i*)	–0.122	–0.196	0.403	0.466	–0.327	–0.357
	(0.609)	(0.634)	(0.455)	(0.463)	(0.261)	(0.266)
Wetness_dest (*j*)	1.770**	1.700**	0.214	0.239	0.384	0.300
	(0.696)	(0.714)	(0.318)	(0.293)	(0.241)	(0.230)
Ag production_orig (*i*)	0.748***	0.747***	0.611***	0.613***	0.462***	0.461***
	(0.113)	(0.114)	(0.085)	(0.084)	(0.064)	(0.063)
Food production_dest (*j*)	–0.162	–0.165	–0.043	–0.045	0.028	0.023
	(0.178)	(0.178)	(0.185)	(0.189)	(0.150)	(0.153)
GDD_home (*h*)	0.123	0.141	0.141	0.126	0.441	0.406
	(0.856)	(0.893)	(0.865)	(0.876)	(0.649)	(0.650)
GDD_orig (*i*)	–1.301	–1.095	0.337	0.227	–0.131	–0.127
	(1.654)	(1.677)	(1.541)	(1.527)	(1.416)	(1.406)
GDD_dest (*j*)	6.559***	6.192***	–2.070*	–1.997*	0.213	0.342

	(1.633)	(1.652)	(1.150)	(1.131)	(1.619)	(1.628)
Precipitation_home (*h*)	0.086 (0.392)	0.099 (0.380)	0.403 (0.253)	0.382 (0.254)	–0.104 (0.132)	–0.120 (0.128)
Precipitation_orig (*i*)	0.083 (0.706)	0.228 (0.700)	–0.404 (0.408)	–0.456 (0.403)	0.120 (0.232)	0.112 (0.237)
Precipitation_dest (*j*)	–0.746 (0.641)	–0.751 (0.652)	–0.067 (0.398)	–0.045 (0.379)	0.185 (0.245)	0.218 (0.238)
Population_dest (*j*)	–1.695* (0.949)	–1.723* (0.963)	1.153 (0.813)	1.171 (0.828)	0.445 (0.580)	0.420 (0.577)
Foreign exports_orig. (*i*)	0.010 (0.027)	0.012 (0.027)	0.024 (0.018)	0.028 (0.019)	0.025 (0.027)	0.027 (0.027)
Foreign imports_dest (*j*)	0.041 (0.034)	0.040 (0.034)	0.017 (0.023)	0.017 (0.023)	0.087** (0.036)	0.087** (0.036)
MRTs	Y	Y	Y	Y	Y	Y
State-pair F.E.	Y	Y	Y	Y	Y	Y
Exporter climate zone-year F.E.	Y	Y	Y	Y	Y	Y
Importer climate zone-year F.E.	Y	Y	Y	Y	Y	Y
R-squared*	0.969	0.969	0.978	0.978	0.983	0.983
Pseudo R-squared	0.963	0.963	0.965	0.965	0.973	0.973
N	5,680	5,680	7,555	7,555	10,940	10,940

Note: The dependent variable is export volume of each SCTG. Each column reports regression results of the gravity equation using (1) drought, and (2) extreme/mild drought. Each gravity includes SCTG-specific foreign exports and imports. All models include fixed effects for state pairs, exporter climate-zone-by-year and importer climate-zone-by-year effects, and multilateral resistance terms (MRTs for distance, neighbor, and home). GDD is growing degree days. R-squared* is the squared correlation between observed and predicted values, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered by state pairs.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F3. Agriculture trade gravity results—capital and labor as proxy for input demand

	Animals and fish (SCTG 01)		Cereal grains (SCTG 02)		Vegetables, fruits, and other crops (SCTG 03)	
	(1)	(2)	(1)	(2)	(1)	(2)
Drought_home (*h*)	0.297 (0.306)		0.297 (0.186)		–0.129 (0.155)	
Drought_orig (*i*)	–0.006 (0.534)		–0.513* (0.268)		–0.053 (0.318)	
Drought_dest (*j*)	–0.618 (0.511)		0.483* (0.279)		0.467 (0.295)	
Extreme drought_home (*h*)		0.241 (0.313)		0.234 (0.188)		–0.137 (0.149)
Mild drought_home (*h*)		0.309 (0.304)		0.285 (0.185)		–0.098 (0.162)
Extreme drought_orig (*i*)		–0.349 (0.536)		–0.736** (0.323)		–0.125 (0.315)
Mild drought_orig (*i*)		0.077 (0.546)		–0.438 (0.315)		–0.121 (0.330)
Extreme drought_dest (*j*)		–0.027 (0.571)		0.586* (0.342)		0.668** (0.299)

Mild drought_dest (*j*)		–0.690		0.520*		0.344
		(0.512)		(0.290)		(0.310)
Wetness_home (*h*)	0.059	0.061	0.013	0.020	0.100	0.117
	(0.339)	(0.333)	(0.148)	(0.151)	(0.167)	(0.177)
Wetness_orig (*i*)	–0.086	–0.158	0.414	0.470	–0.319	–0.347
	(0.617)	(0.643)	(0.453)	(0.460)	(0.260)	(0.266)
Wetness_dest (*j*)	1.801***	1.735**	0.188	0.212	0.300	0.205
	(0.696)	(0.716)	(0.329)	(0.307)	(0.259)	(0.248)
Ag production_orig (*i*)	0.747***	0.747***	0.601***	0.599***	0.460***	0.460***
	(0.115)	(0.115)	(0.087)	(0.086)	(0.067)	(0.067)
Food capital_dest (*j*)	0.063	0.057	–0.314	–0.319	0.391***	0.386***
	(0.208)	(0.209)	(0.218)	(0.222)	(0.145)	(0.144)
Food labor_dest (*j*)	0.144	0.157	0.364	0.371	–0.670*	–0.675*
	(0.499)	(0.498)	(0.405)	(0.411)	(0.389)	(0.388)
GDD_home (*h*)	0.080	0.091	–0.025	–0.049	0.491	0.481
	(0.826)	(0.864)	(0.902)	(0.934)	(0.631)	(0.630)
GDD_orig (*i*)	–1.389	–1.165	0.288	0.186	–0.134	–0.132
	(1.656)	(1.679)	(1.542)	(1.529)	(1.432)	(1.424)
GDD_dest (*j*)	6.722***	6.342***	–2.239*	–2.181*	0.217	0.355
	(1.653)	(1.677)	(1.182)	(1.168)	(1.638)	(1.642)
Precipitation_home (*h*)	0.064	0.087	0.401	0.376	–0.106	–0.108
	(0.392)	(0.383)	(0.266)	(0.266)	(0.128)	(0.127)
Precipitation_orig (*i*)	–0.003	0.148	–0.437	–0.486	0.138	0.133
	(0.719)	(0.714)	(0.411)	(0.406)	(0.233)	(0.237)
Precipitation_dest (*j*)	–0.765	–0.771	–0.047	–0.030	0.185	0.227
	(0.648)	(0.660)	(0.400)	(0.383)	(0.257)	(0.249)
Population_dest (*j*)	–1.672	–1.706	0.865	0.865	0.876	0.865
	(1.067)	(1.078)	(0.737)	(0.748)	(0.554)	(0.550)
MRTs	Y	Y	Y	Y	Y	Y
State-pair F.E.	Y	Y	Y	Y	Y	Y
Exporter climate zone-year F.E.	Y	Y	Y	Y	Y	Y
Importer climate zone-year F.E.	Y	Y	Y	Y	Y	Y
R-squared*	0.969	0.969	0.977	0.978	0.984	0.984
Pseudo R-squared	0.963	0.963	0.965	0.965	0.973	0.973
N	5,680	5,680	7,555	7,555	10,940	10,940

Note: The dependent variable is export volume of each SCTG. Each column reports regression results of the gravity equation using (1) drought, and (2) extreme/mild drought. Manufactured food sector capital and labor are included as proxies for input demand. All models include fixed effects for state pairs, exporter climate-zone-by-year and importer climate-zone-by-year effects, and multilateral resistance terms (MRTs for distance, neighbor, and home). GDD is growing degree days. R-squared* is the squared correlation between observed and predicted values, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered by state pairs.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F4. First stage results—from gravity-based instruments of drought

	à la F&G (1)	Int. trade (2)	Demand cond. (3)	Gravity demand: K&L (4)	SCTG 04–07 (5)

Panel A. Dependent variable: observed animals and fish (SCTG 01)					
Predicted agricultural inputs (instruments)					
SCTG 01	1.158***	1.163***	1.142***	1.166***	1.167***
	(0.125)	(0.121)	(0.115)	(0.119)	(0.120)
SCTG 02	–0.376	–0.332	–0.361	–0.329	–0.330
	(0.340)	(0.332)	(0.329)	(0.321)	(0.321)
SCTG 03	0.254	0.140	0.049	0.154	0.111
	(0.216)	(0.221)	(0.201)	(0.213)	(0.230)
Capital	–0.341	–0.133	0.319	–0.703	0.104
	(0.759)	(0.783)	(0.830)	(0.818)	(0.514)
Imported SCTG 01		–0.063			
		(0.098)			
Imported SCTG 02		–0.025			
		(0.029)			
Imported SCTG 03		–0.075			
		(0.148)			
Intermediate demand_food			–0.851		
			(0.622)		
Household demand_population			0.918		
			(1.053)		
SW *F*-statistics	109.63	136.91	111.06	115.68	121.48
Reduced-form *F*-statistics	34.01	37.83	39.91	39.52	38.80
Panel B. Dependent variable: observed cereal grains (SCTG 02)					
Predicted agricultural inputs (instruments)					
SCTG 01	0.078	0.067	0.030	0.056	0.065
	(0.128)	(0.102)	(0.091)	(0.099)	(0.097)
SCTG 02	0.832***	0.875***	0.874***	0.854***	0.872***
	(0.121)	(0.110)	(0.111)	(0.106)	(0.110)
SCTG 03	0.344	0.381	0.316	0.365	0.358
	(0.251)	(0.242)	(0.233)	(0.233)	(0.228)
Capital	0.246	0.320	0.277	0.347	–0.453
	(0.693)	(0.626)	(0.946)	(0.757)	(0.647)
Imported SCTG 01		–0.121			
		(0.085)			
Imported SCTG 02		–0.104**			
		(0.045)			
Imported SCTG 03		0.115			
		(0.128)			
Intermediate demand_food			–0.213		
			(0.987)		
Household demand_population			0.750		
			(1.127)		
SW *F*-statistics	33.91	46.58	44.12	42.24	43.26
Reduced-form *F*-statistics	23.00	28.05	26.00	28.97	27.12
Panel C. Dependent variable: observed vegetables, fruits, and other crops (SCTG 03)					
Predicted agricultural inputs (instruments)					
SCTG 01	0.002	–0.027	–0.010	–0.037	–0.032
	(0.078)	(0.070)	(0.074)	(0.075)	(0.077)
SCTG 02	0.048	0.066	0.056	0.061	0.064

	(0.069)	(0.066)	(0.070)	(0.067)	(0.073)
SCTG 03	0.916*** (0.140)	0.979*** (0.132)	0.969*** (0.144)	0.895*** (0.118)	0.941*** (0.123)
Capital	0.101 (0.376)	–0.019 (0.347)	0.299 (0.426)	–0.527 (0.406)	–0.147 (0.323)
Imported SCTG 01		–0.066 (0.042)			
Imported SCTG 02		0.010 (0.023)			
Imported SCTG 03		0.018 (0.092)			
Intermediate demand_food			–0.416 (0.287)		
Household demand_population			–0.467 (0.756)		
SW *F*-statistics	58.62	81.95	65.57	75.94	74.59
Reduced-form *F*-statistics	15.10	22.46	17.64	21.50	21.23
State F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
N	240	240	240	240	240

Note: The dependent variable is observed agricultural input flows (SCTG 01–03), treated as endogenous and instrumented using predicted trade values from gravity model estimates (SCTG 01–03) using drought without threshold. Each column reports estimates of (1) model à la F&G, (2) model with international trade, (3) model conditional on demand, (4) the specification using food sector capital and labor as proxies for input demand in gravity, and (5) the SCTG 04–07 output. Each panel reports results for animals and fish (A), cereal grains (B), and other crops (B). Labor is excluded, as all variables from second-stage production function are normalized by labor to impose constant returns to scale. Sander and Windmeijer (SW) *F*-statistics are reported as tests for weak instruments with multiple endogenous regressors. Reduced-form *F*-statistics indicates joint significance of excluded instruments. All *F*-statistics exceed the standard threshold of 10. Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F5. Second-stage results—from gravity-based instruments of drought

	à la F&G (1)	Int. trade (2)	Demand cond. (3)	Gravity demand: K&L (4)	SCTG 04–07 (5)
Animals and fish (SCTG 01)	–0.010 (0.015)	–0.008 (0.012)	–0.002 (0.017)	–0.005 (0.013)	–0.012 (0.012)
Cereal grains (SCTG 02)	0.052 (0.033)	0.052* (0.029)	0.063* (0.033)	0.068** (0.034)	0.048 (0.032)
Vegetables, fruits, and other (SCTG 03)	0.048 (0.065)	0.046 (0.053)	0.042 (0.053)	0.019 (0.070)	0.063 (0.059)
Capital	0.183* (0.107)	0.189* (0.106)	0.154 (0.133)	0.187* (0.107)	0.229* (0.137)
Labor	0.638*** (0.155)	0.633*** (0.144)	0.641*** (0.153)	0.650*** (0.160)	0.573*** (0.201)
Imported SCTG 01		–0.003 (0.019)			
Imported SCTG 02		0.005 (0.007)			

Imported SCTG 03		–0.032 (0.025)			
Intermediate demand_food			0.068 (0.151)		
Household demand_population			–0.158 (0.355)		
State F.E.	Y	Y	Y		Y
Year F.E.	Y	Y	Y		Y
R-squared*	0.689	0.693	0.672	0.674	0.650
N	240	240	240	240	240

Note: The dependent variable is the output of food manufacturing in 2012 U.S. dollars when the agricultural inputs (SCTG 01–03) are instrumented with gravity-instruments using drought without threshold. Each column reports estimates of the (1) model à la F&G, (2) model with international trade, (3) model conditional on demand, (4) the specification using food sector capital and labor as proxies for input demand in gravity, and (5) the SCTG 04–07 output. All estimations include two-way fixed effects (F.E.). R-squared* is the squared coefficient of correlation between the observed and predicted dependent variables, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F6. First-stage results—from gravity-based instruments of extreme/mild drought

	à la F&G (1)	Int. trade (2)	Demand cond. (3)	Gravity demand: K&L (4)	SCTG 04–07 (5)
Panel A. Dependent variable: observed animals and fish (SCTG 01)					
Predicted agricultural inputs (instruments)					
SCTG 01	1.145*** (0.117)	1.154*** (0.118)	1.136*** (0.113)	1.156*** (0.117)	1.157*** (0.117)
SCTG 02	–0.375 (0.343)	–0.333 (0.333)	–0.370 (0.332)	–0.334 (0.322)	–0.339 (0.325)
SCTG 03	0.283 (0.222)	0.178 (0.225)	0.092 (0.203)	0.189 (0.213)	0.147 (0.229)
Capital	–0.335 (0.766)	–0.146 (0.781)	0.317 (0.826)	–0.722 (0.819)	0.112 (0.510)
Imported SCTG 01		–0.062 (0.096)			
Imported SCTG 02		–0.025 (0.028)			
Imported SCTG 03		–0.075 (0.149)			
Intermediate demand_food			–0.847 (0.617)		
Household demand_population			0.838 (1.072)		
SW *F*-statistics	108.91	133.55	107.73	108.26	116.97
Reduced-form *F*-statistics	36.71	38.90	40.53	40.36	39.97
Panel B. Dependent variable: observed cereal grains (SCTG 02)					
Predicted agricultural inputs (instruments)					
SCTG 01	0.076 (0.126)	0.066 (0.101)	0.027 (0.090)	0.053 (0.097)	0.062 (0.097)

SCTG 02	0.831***	0.867***	0.868***	0.849***	0.865***
	(0.122)	(0.111)	(0.110)	(0.106)	(0.109)
SCTG 03	0.350	0.397	0.336	0.387	0.379
	(0.250)	(0.244)	(0.238)	(0.239)	(0.232)
Capital	0.241	0.333	0.273	0.334	–0.467
	(0.690)	(0.620)	(0.949)	(0.756)	(0.647)
Imported SCTG 01		–0.121			
		(0.085)			
Imported SCTG 02		–0.104**			
		(0.045)			
Imported SCTG 03		0.115			
		(0.130)			
Intermediate demand_food			–0.217		
			(0.988)		
Household demand_population			0.760		
			(1.131)		
SW *F*-statistics	32.85	44.99	43.03	41.11	42.50
Reduced-form *F*-statistics	22.66	27.30	25.81	28.44	26.84
Panel C. Dependent variable: observed vegetables, fruits, and other crops (SCTG 03)					
Predicted agricultural inputs (instruments)					
SCTG 01	0.002	–0.029	–0.013	–0.039	–0.034
	(0.080)	(0.071)	(0.076)	(0.076)	(0.078)
SCTG 02	0.045	0.061	0.051	0.057	0.059
	(0.068)	(0.065)	(0.069)	(0.066)	(0.072)
SCTG 03	0.915***	0.987***	0.975***	0.904***	0.949***
	(0.138)	(0.131)	(0.142)	(0.117)	(0.121)
Capital	0.097	–0.013	0.290	–0.533	–0.166
	(0.370)	(0.337)	(0.425)	(0.400)	(0.319)
Imported SCTG 01		–0.068			
		(0.042)			
Imported SCTG 02		0.009			
		(0.024)			
Imported SCTG 03		0.011			
		(0.093)			
Intermediate demand_food			–0.409		
			(0.287)		
Household demand_population			–0.425		
			(0.743)		
SW *F*-statistics	57.83	79.12	65.45	71.84	74.36
Reduced-form *F*-statistics	15.58	23.03	18.12	22.13	22.07
State F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
N	240	240	240	240	240

Note: The dependent variable is observed agricultural input flows (SCTG 01–03), treated as endogenous and instrumented using predicted trade values from gravity model estimates (SCTG 01–03) using extreme/mild drought. Each column reports estimates of the (1) model à la F&G, (2) model with international trade, (3) model conditional on demand, (4) the specification using food sector capital and labor as proxies for input demand in gravity, and (5) the SCTG 04–07 output. Each panel reports results for animals and fish (A), cereal grains (B), and other crops (B). Labor is excluded, as all variables from second-stage production function are normalized by labor to impose constant returns to scale. Sander and Windmeijer (SW) *F*-statistics are reported as tests for weak instruments with multiple endogenous regressors. Reduced-form *F*-statistics indicate joint significance of excluded instruments. All *F*-statistics exceed the standard threshold of 10. Standard errors are clustered at the

state level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table F7. Second-stage results—from gravity-based instruments of extreme/mild drought

	à la F&G (1)	Int. trade (2)	Demand cond. (3)	Gravity demand: K&L (4)	SCTG 04–07 (5)
Animals and fish (SCTG 01)	–0.010 (0.015)	–0.008 (0.012)	–0.002 (0.017)	–0.006 (0.013)	–0.012 (0.012)
Cereal grains (SCTG 02)	0.052* (0.033)	0.051* (0.029)	0.063* (0.033)	0.068** (0.034)	0.049 (0.032)
Vegetables, fruits, and other (SCTG 03)	0.048 (0.065)	0.048 (0.054)	0.042 (0.055)	0.020 (0.072)	0.063 (0.060)
Capital	0.182* (0.108)	0.189* (0.106)	0.153 (0.134)	0.186* (0.108)	0.229* (0.137)
Labor	0.636*** (0.154)	0.631*** (0.144)	0.640*** (0.153)	0.649*** (0.162)	0.570*** (0.202)
Imported SCTG 01		–0.003 (0.019)			
Imported SCTG 02		0.005 (0.007)			
Imported SCTG 03		–0.032 (0.025)			
Intermediate demand_food			0.069 (0.152)		
Household demand_population			–0.157 (0.355)		
State F.E.	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y
R-squared*	0.689	0.693	0.671	0.674	0.649
N	240	240	240	240	240

Note: The dependent variable is the output of food and beverage manufacturing in 2012 dollars when the agricultural inputs (SCTG 01–03) are instrumented with gravity-instruments using extreme/mild drought. Each column reports estimates of the (1) model à la F&G, (2) model with international trade, (3) model conditional on demand, (4) the specification using food sector capital and labor as proxies for input demand in gravity, and (5) the SCTG 04–07 output. All estimations include two-way fixed effects (F.E.). R-squared* is the squared coefficient of correlation between the observed and predicted dependent variables, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered at the state level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix G. Robustness checks—using various elasticities of substitution

Here we examine the robustness of our results to alternative elasticities of substitution between local and imported inputs, applying the same two-stage instrumental variable approach described in the *Materials and Methods* section of the main manuscript. The results using gravity-based instruments with drought for stage 1 and 2 are reported in Tables G1 and G2, respectively. The same approach but using instruments estimated with extreme/mild drought are reported in Tables G3 and G4. We find that, across all specifications, the output elasticity for the sub-aggregate of cereal grains (SCTG 02) remains consistently close to 0.12, which demonstrates the robustness of our conclusions under varying substitution levels.

Table G1. First-stage results—from gravity-based instruments of drought

	$\sigma = 1.2$ (1)	$\sigma = 1.5$ (2)	$\sigma = 2$ (3)
Panel A. Dependent variable: observed animals and fish (SCTG 01)			
Predicted agricultural inputs (instruments)			
SCTG 01	1.196*** (0.108)	1.208*** (0.099)	1.207*** (0.092)
SCTG 02	–0.323 (0.318)	–0.307 (0.305)	–0.298 (0.291)
SCTG 03	0.077 (0.186)	0.067 (0.171)	0.060 (0.160)
Capital	–0.024 (0.351)	0.026 (0.311)	0.064 (0.280)
SW *F*-statistics	136.03	185.18	218.79
Reduced-form *F*-statistics	55.85	70.65	83.51
Panel B. Dependent variable: observed cereal grains (SCTG 02)			
Predicted agricultural inputs (instruments)			
SCTG 01	0.006 (0.093)	0.024 (0.093)	0.025 (0.093)
SCTG 02	0.878*** (0.106)	0.848*** (0.100)	0.828*** (0.098)
SCTG 03	0.377 (0.253)	0.299 (0.215)	0.268 (0.198)
Capital	0.120 (0.321)	0.025 (0.309)	–0.025 (0.301)

SW *F*-statistics	43.89	42.19	40.51
Reduced-form *F*-statistics	25.99	31.69	32.16
Panel C. Dependent variable: observed vegetables, fruits, and other crops (SCTG 03)			
Predicted agricultural inputs (instruments)			
SCTG 01	–0.024 (0.071)	–0.016 (0.066)	–0.008 (0.063)
SCTG 02	0.078 (0.075)	0.088 (0.080)	0.095 (0.084)
SCTG 03	0.969*** (0.127)	0.989*** (0.131)	1.006*** (0.136)
Capital	–0.020 (0.187)	–0.022 (0.187)	–0.024 (0.187)
SW *F*-statistics	62.58	74.99	78.69
Reduced-form *F*-statistics	22.46	24.01	25.58
State F.E.	Y	Y	Y
Year F.E.	Y	Y	Y
N	240	240	240

Note: The dependent variable is observed agricultural input flows (SCTG 01–03) treated as endogenous and instrumented using the predicted trade values from the gravity model estimates (SCTG 01–03) using drought. Each column reports the estimates of stage 2 with elasticities of substitution equal to: (1) 1.2, (2) 1.5, and (3) 2. Each panel reports the results for animals and fish (A), cereal grains (B), and other crops (B). Labor is excluded as all the variables from the second-stage production function are normalized by labor to impose constant returns to scale. Sander and Windmeijer (SW) *F*-statistics are reported as tests for weak instruments with multiple endogenous regressors. Reduced-form *F*-statistics indicate joint significance of excluded instruments. All *F*-statistics exceed the standard threshold of 10. Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table G2. Second-stage results— from gravity-based instruments of drought

	$\sigma = 1.2$ (1)	$\sigma = 1.5$ (2)	$\sigma = 2$ (3)
Animals and fish (SCTG 01)	–0.006 (0.024)	–0.005 (0.023)	–0.004 (0.022)
Cereal grains (SCTG 02)	0.121* (0.066)	0.122* (0.069)	0.120* (0.070)
Vegetables, fruits, and other (SCTG 03)	0.062 (0.129)	0.068 (0.119)	0.070 (0.113)
Capital	0.178 (0.110)	0.186* (0.108)	0.189* (0.108)
Labor	0.645*** (0.160)	0.630*** (0.149)	0.625*** (0.143)
State F.E.	Y	Y	Y
Year F.E.	Y	Y	Y
R-squared*	0.675	0.687	0.692
N	240	240	240

Note: The dependent variable is the output of food and beverage manufacturing in 2012 dollars when the agricultural inputs (SCTG 01–03) are instrumented with gravity-instruments using drought. Each column reports the estimates of stage 2 with elasticities of substitution equal to: (1) 1.2, (2) 1.5, and (3) 2. All estimations include two-way fixed effects (F.E.). R-squared* is the squared coefficient of correlation between the observed and predicted dependent variables, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table G3. First-stage results—from gravity-based instruments of extreme/mild drought

	$\sigma = 1.2$ (1)	$\sigma = 1.5$ (2)	$\sigma = 2$ (3)
Panel A. Dependent variable: observed animals and fish (SCTG 01)			
Predicted agricultural inputs (instruments)			
SCTG 01	1.188***	1.200***	1.202***
	(0.106)	(0.098)	(0.091)
SCTG 02	–0.331	–0.315	–0.304
	(0.321)	(0.306)	(0.292)
SCTG 03	0.114	0.101	0.090
	(0.187)	(0.172)	(0.162)
Capital	–0.029	0.021	0.060
	(0.351)	(0.311)	(0.280)
SW *F*-statistics	128.99	176.45	207.46
Reduced-form *F*-statistics	56.75	70.95	83.18
Panel B. Dependent variable: observed cereal grains (SCTG 02)			
Predicted agricultural inputs (instruments)			
SCTG 01	0.006	0.024	0.025
	(0.093)	(0.092)	(0.092)
SCTG 02	0.871***	0.842***	0.822***
	(0.105)	(0.099)	(0.097)
SCTG 03	0.397	0.312	0.277
	(0.258)	(0.219)	(0.201)
Capital	0.117	0.024	–0.026
	(0.321)	(0.310)	(0.302)
SW *F*-statistics	43.19	41.58	39.80
Reduced-form *F*-statistics	26.00	31.73	32.31
Panel C. Dependent variable: observed vegetables, fruits, and other crops (SCTG 03)			
Predicted agricultural inputs (instruments)			
SCTG 01	–0.025	–0.016	–0.008
	(0.071)	(0.067)	(0.064)
SCTG 02	0.074	0.085	0.093
	(0.074)	(0.079)	(0.083)
SCTG 03	0.978***	0.997***	1.013***
	(0.125)	(0.129)	(0.134)
Capital	–0.022	–0.025	–0.027
	(0.184)	(0.185)	(0.186)
SW *F*-statistics	61.04	75.79	80.62
Reduced-form *F*-statistics	23.21	24.75	26.26
State F.E.	Y	Y	Y
Year F.E.	Y	Y	Y
N	240	240	240

Note: The dependent variable is observed agricultural input flows (SCTG 01–03) treated as endogenous and instrumented using the predicted trade values from the gravity model estimates (SCTG 01–03) using extreme/mild drought. Each column reports estimates of stage 2 with elasticities of substitution equal to: (1) 1.2, (2) 1.5, and (3) 2. Each panel reports results for animals and fish (A), cereal grains (B), and other crops (B). Labor is excluded as all the variables from the second-stage production function are normalized by labor to impose constant returns to scale. Sander and Windmeijer (SW) *F*-statistics are reported as tests for weak instruments with multiple endogenous regressors. Reduced-form *F*-statistics indicate joint significance of excluded instruments. All *F*-statistics exceed the standard threshold of 10. Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table G4. Second-stage results— from gravity-based instruments of extreme/mild drought

	$\sigma = 1.2$ (1)	$\sigma = 1.5$ (2)	$\sigma = 2$ (3)
Animals and fish (SCTG 01)	–0.007	–0.006	–0.005
	(0.024)	(0.023)	(0.022)
Cereal grains (SCTG 02)	0.123*	0.124*	0.122*
	(0.067)	(0.070)	(0.071)
Vegetables, fruits, and other (SCTG 03)	0.063	0.069	0.071
	(0.134)	(0.123)	(0.116)
Capital	0.178	0.186*	0.189*
	(0.111)	(0.109)	(0.108)
Labor	0.643***	0.627***	0.623***
	(0.161)	(0.149)	(0.143)
State F.E.	Y	Y	Y
Year F.E.	Y	Y	Y
R-squared*	0.673	0.685	0.691
N	240	240	240

Note: The dependent variable is the output of food and beverage manufacturing in 2012 dollars when the agricultural inputs (SCTG 01–03) are instrumented with gravity-instruments using extreme/mild drought. Each column reports estimates of stage 2 with elasticities of substitution equal to: (1) 1.2, (2) 1.5, and (3) 2. All estimations include two-way fixed effects (F.E.). R-squared* is the squared coefficient of correlation between the observed and predicted dependent variables, used as a measure of fit (Larch et al., 2019; Green and Santos Silva, 2024). Standard errors are clustered at the state level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

SI References

Anderson, J. E., and van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, *93*(1), 170–192. https://doi.org/10.1257/000282803321455214

Anderson, J. E., and Yotov, Y. V. (2016). Terms of trade and global efficiency effects of free trade agreements, 1990-2002. *Journal of International Economics*, *99*, 279–298. https://doi.org/10.1016/j.jinteco.2015.10.006

Baier, S. L., and Bergstrand, J. H. (2009). Bonus vetus OLS: A simple method for approximating international trade-cost effects using the gravity equation. *Journal of International Economics*, *77*(1), 77–85. https://doi.org/10.1016/j.jinteco.2008.10.004

Bridge Between 2002 NAICS and 1997 NAICS: 2002. (2006). U.S. Census Bureau. https://www2.census.gov/library/publications/economic-census/2002/core-business-statistics-series/ec0200cbdg.pdf

Crop Acreage Data. (2022). U.S. Department of Agriculture Farm Service Agency. https://www.fsa.usda.gov/tools/informational/freedom-information-act-foia/electronic-reading-room/frequently-requested/crop-acreage-data

Dall'erba, S., Chen, Z., and Nava, N. J. (2021). U.S. Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit. *American Journal of Agricultural Economics*, *103*(5), 1720–1741. https://doi.org/10.1111/ajae.12204

Escarcha, J. F., Lassa, J. A., and Zander, K. K. (2018). Livestock under climate change: A systematic review of impacts and adaptation. *Climate*, *6*(3), 1–17. https://doi.org/10.3390/cli6030054

Felbermayr, G., and Gröschl, J. (2013). Natural disasters and the effect of trade on income: A new panel IV approach. *European Economic Review*, *58*, 18–30. https://doi.org/10.1016/j.euroecorev.2012.11.008

Green, N. J. D., and Santos Silva, J. M. C. (2024). *A Cautionary Note on the Assessment of Goodness-of-Fit in Models Estimated by PPML [Preprint]*. https://doi.org/10.2139/ssrn.4888273

IMPLAN. (2020). *Data, IMPLAN Group LLC, IMPLAN System*.

Larch, M., Wanner, J., Yotov, Y. V., and Zylkin, T. (2019). Currency Unions and Trade: A PPML Re-assessment with High-dimensional Fixed Effects. *Oxford Bulletin of Economics and Statistics*, *81*(3), 487–510. https://doi.org/10.1111/obes.12283

Lesk, C., Rowhani, P., and Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84–87. https://doi.org/10.1038/nature16467

Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J. N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, *13*(9), 4349–4383. https://doi.org/10.5194/essd-13-4349-2021

Peri, G. (2012). The Effect Of Immigration On Productivity: Evidence From U.S. States. *The Review of Economics and Statistics*, *94*(1), 348–358.

https://doi.org/10.1162/REST_a_00137

PRISM Climate Group. (2024). *Descriptions of PRISM Spatial Climate Datasets for the Conterminous United States*. https://prism.oregonstate.edu/documents/PRISM_datasets.pdf

Ray, R. L., Fares, A., and Risch, E. (2018). Effects of Drought on Crop Production and Cropping Areas in Texas. *Agricultural & Environmental Letters*, *3*(1), 1–5. https://doi.org/10.2134/ael2017.11.0037

Soybeans - Production. (2023). U.S. Department of Agriculture. https://quickstats.nass.usda.gov/

Thrasher, B., Wang, W., Michaelis, A., Melton, F., Lee, T., and Nemani, R. (2022). NASA Global Daily Downscaled Projections, CMIP6. *Scientific Data*, *9*(1), 1–6. https://doi.org/10.1038/s41597-022-01393-4

Usual Planting and Harvesting Dates for US Fields Crops. (2010). *U.S. Department of Agriculture National Agricultural Statistics Service, Agricultural Handbook*, *628*. https://usda.library.cornell.edu/concern/publications/vm40xr56k

Yotov, Y. V., Piermartini, R., Monteiro, J.-A., and Larch, M. (2016). *An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model*. World Trade Organization.