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A model of the U.S. food system: What are the determinants of the state vulnerabilities to production shocks and supply chain disruptions?

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Abstract: We adapt a Ricardian general equilibrium model to the setting of U.S. domestic agri-food trade to assess states' vulnerability to adverse production shocks and supply chain disruptions. To this end, we analyze how domestic crop supply chains depend on fundamental state-level comparative advantages – which reflect underlying differences in states' cost-adjusted productivity levels – and thereby illustrate the capacity of states to adapt to and mitigate the impacts of such disruptions to the U.S. agricultural sector. Based on the theoretical framework and our estimates of the model's structural parameters obtained using data on U.S. production, consumption, and domestic trade in crops, we undertake simulations to characterize the welfare implications of counterfactual scenarios depicting disruptions to (1) states' agricultural productive capacity, and (2) interstate supply linkages. Our results emphasize that the distributional impacts of domestic supply chain disruptions hinge on the extent of individual states' agricultural productive capacities, and that the capacity for states to mitigate the impacts of adverse production shocks through trade relies on the degree to which states are able to substitute local production shortfalls by sourcing crops from other states.

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1. Introduction

The tradeoffs between self-sufficiency versus reliance on external sources in meeting regions' food needs have long been understood; however, debates over how best to structure food supply chains in order to maximize their resiliency continue to persist. Proponents of inward-oriented food systems emphasize the benefits of self-reliance, and recent work by Biedny, Malone and Lusk (2020) finds that in spite of the sharp polarization of American political attitudes, beliefs from either end of the ideological spectrum tend to favor food systems founded on proximate supply sources as the best means with which to promote food system resiliency.[1] A common claim from proponents of such approaches is that as the distance between regions and their food sources increases, the disconnect between the adverse environmental consequences of food production widens, hindering regulators' efforts to internalize the negative externalities of agricultural production (Clapp, 2015).[2] Most recently, the challenges created for the U.S. food system from the onset of the COVID-19 pandemic led to wasted production, increases in food prices, and disruptions to key links in the food supply chain (Hobbs, 2020; Thilmany et al., 2020; Martinez, Maples, and Benavidez, 2021). Other recent disruptions to both international and domestic supply chains have highlighted their susceptibility to disruptions at critical points in the system. For instance, the upending of global trade networks caused by the recent temporary closure of the Suez Canal illustrated how disruption at a single critical point can cause widespread disruption, while at the domestic level, food prices can potentially raise due to this short-run fall in supply.

In contrast, economists have long emphasized the ways in which specialization and interdependence through trade can facilitate access to efficiently produced products (Krugman, 1981; Eaton and Kortum, 2002; Arkolakis, Costinot, and Rodríguez-Clare, 2012) and promote resiliency in the food system (Reimer and Li, 2009, 2010). Classical theories of trade and specialization make clear that food systems will be most efficient when they allow for regions to exploit differences in comparative advantage. Perhaps most importantly, the permanent availability of external food sources ensures that disruptions to local supply can be mitigated through reliance on trade partners (Ferguson and Gars, 2020; Dall'Erba, Chen, and Nava, 2021).

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[1] Proponents of policies that promote local agriculture also raise environment and health concerns in addition to concerns relating to the resiliency of outward-oriented food systems emphasizing reliance on distant sources of supply (DuPuis and Goodman, 2005; Levkoe, 2011; Marsden, 2013).

[2] In Blay-Palmer et al. (2013), several examples of bottom-up approaches to the promotion of local agriculture are discussed.

Therefore, while inward-oriented food system approaches emphasize the disadvantages of reliance on distant supply sources, outward-oriented strategies for food system design tend to highlight the benefits arising from trade and specialization alongside the capacity of such systems to mitigate the impacts of negative shocks to one's own production through interdependence and trade.

Due to the complexity of the U.S. food system and the importance of domestic supply and demand relationships in U.S. agriculture, the optimal design of the food system necessitates an appraisal of inter- and intra-state reliance in order to assess the advantages and disadvantages of each. However, while a broad assortment of work has addressed these issues in appraising food systems at the international level (Grant, and Lambert, 2008; Reimer and Li, 2009, 2010; Martin, 2018), a paucity of work on food systems and trade relationships at the domestic level prevents researchers from analyzing these same important questions of resilience and efficacy (Smith *et al.,* 2017; Lin *et al.,* 2019). In this paper, therefore, we undertake a quantitative analysis of the U.S. domestic food system by adapting a structural, general equilibrium model of trade based on Ricardian comparative advantage and gravity relationships to U.S. states' supply and demand for primary crops in order to quantify the efficacy of various strategies in promoting food systems' efficiency and resilience.

An ideal approach with which to jointly consider supply, demand, and trade relationships between regions is the gravity model, in which bilateral trade is expressed as a function of the size of supply and demand in the exporter and importer, respectively, and both bilateral and multilateral barriers to trade. Approaches based on gravity models are ideal for assessing the welfare and consumption implications of various policy counterfactuals in that they are theoretically founded and can be derived based on either demand-based (Anderson, 1979; Bergstrand, 1985; Anderson and van Wincoop, 2003) or supply-based (Chaney, 2008; Chor, 2010) formulations. In settings where regions' productivities – and thus, their comparative advantages, and the scope for specialization and interdependence – are the central focus, supply-side analyses offer the ideal approach with which to assess the resilience and efficiency of trade networks. Along these lines, the seminal work of Eaton and Kortum (2002) (henceforth, EK) develops a model which considers the producers' relative comparative advantages as reflected by differences in cost-adjusted fundamental productivities, and which further yields a tractable framework with which to empirically assess welfare, consumption, and trade under alternative counterfactuals. We therefore

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adapt the theoretical framework of EK to the setting of the domestic U.S. trade in crops in order to analyze and explore the properties of the U.S. food system.

Despite its widespread use in the broader trade literature, only a few empirical studies of food and agriculture base their analyses on a Ricardian notion of comparative advantage. Similar to our work is that of Reimer and Li (2009, 2010) that exploit this formulation at the international level to study how yield variability across countries determines the welfare of consumers, finding that openness to trade increases countries' welfare whenever they experience adverse yield conditions. Recent work by Heerman (2020) incorporates agro-ecological conditions into the Ricardian setting as a determinant of productivity, while Devadoss, Ugwuanyi, and Ridley (2021) augment the Ricardian setting with Heckscher-Ohlin-style endowment effects. In a similar fashion, we adapt and estimate the EK model in order to study U.S. states' food vulnerability in the existing domestic food system and to assess the efficacy of the system under various policy counterfactuals.

To analyze these issues, we consider two distinct counterfactual scenarios. First, the impacts of shocks to individual states' productivities are simulated as arising through reductions in each state's agricultural capacity – a structural parameter (described in detail below) that governs each state's agricultural productivity. Second, food supply chain disruptions are modeled by significantly increasing the costs of interstate trade between each pair of states. To assess the distributional impacts under these various counterfactuals, we construct a ranking of relative comparative advantage to pinpoint how states' underlying relative productivity levels as a key determinant of food vulnerability in each of our simulations. We find that the distribution of welfare losses depends on each state's ability to substitute consumption sources, which depends on both its own fundamental productivity and on its ability to efficiently source crops from other states.

Our work makes three primary contributions to the literature on food security and trade. First, our approach is based on a comprehensive but tractable model of the U.S. market for crops that can be employed to analyze a large array of counterfactuals concerning food security in the United States. This approach accounts for the heterogeneity of farmers' productivities by incorporating and estimating producer-specific efficiency terms. In addition, we recognize food processors and other intermediate users as the main consumers of farmers' production and isolate their substitution effect. Secondly, we construct a state-level ranking of relative comparative advantage using data on domestic interstate trade. While most Ricardian trade studies recognize competitiveness (i.e.,

the exporter's relative cost-adjusted productivity) and openness (i.e., the importer's relative ease of access to externally sourced products) in their applications, researchers do not exploit the ranking and rather focus on the decomposition of the determinants of productivity and comparative advantage. We use this ranking of relative comparative advantage in the U.S. food system to study the mechanisms that shape welfare losses in our food vulnerability counterfactuals.

Due to the challenges associated with collecting domestic trade data, our third and final contribution relates to expanding the body of work analyzing trade in domestic settings, a literature that remains nascent in spite of the profound importance of domestic trading relationships in the United States and elsewhere. One benefit afforded by this setting is that U.S. domestic trade is absent of non-market barriers such as tariffs, and focusing on domestic trade thereby presents the opportunity to study the market mechanisms that govern trade and welfare distributions absent of policy confounders. To our knowledge, our study is the first to adopt a general equilibrium Ricardian approach to modeling productivity and domestic trade in agriculture at a regional (sub-national) level in a modern setting.[3]

The remainder of the paper is organized as follows. The next section describes our extension of the formulation of EK, and its implications for the U.S. domestic market for crops. Section 3 presents our empirical strategy. First, we describe how we process the data to capture the economic realities of the U.S. domestic crop market. We then econometrically estimate the structural model parameters necessary for our post-estimation simulations and conduct a decomposition of each state's comparative advantage. In section 4, we describe our simulation strategy and then present and discuss the results from our counterfactuals. Finally, we offer concluding remarks in section 5.

2. A Ricardian trade model of U.S. domestic crop production

As described earlier, we adapt the canonical EK formulation to the setting of domestic U.S. crop trade in order to assess how welfare, production, and consumption respond to disruptions in the U.S. domestic food system. In this section, we recount the key features of the EK model and describe how its components correspond to the U.S. domestic system, and how the modelling framework will allow us to (1) tie the model's equilibrium relationships on production,

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[3] Donaldson (2018) employs a Ricardian model of agricultural productivity and sub-national trade in the context of colonial India.

consumption, trade, and welfare to observed data, and (2) empirically estimate the model's fundamental parameters in the setting of U.S. domestic trade in crops.

On the supply side, we denote producers (farmers) by i and refer to them as exporters, producers and the origin of the commodity interchangeably. Producers operate under different weather, technology and land characteristics across U.S. states.[4] We capture their heterogeneity with a land productivity term denoted as $a_i(l)$, where l indicates commodity (with $l \in [0,1]$), a technological productivity-augmenting factor denoted as z_i, and farmers' production costs denoted as c_i (Eaton and Kortum, 2002; Heerman, 2020). We denote final prices as $P_{ij}(l)$ and bilateral trade costs as t_{ij}. They distinguish the source of the commodity i and the location of consumption j.[5] Assuming constant-returns-to-scale technology and perfectly competitive output and input markets, the final price is related to costs of production, the producer's efficiency, and bilateral trade costs as given by:

$$P_{ij}(l) = \frac{c_i}{z_i a_i(l)} t_{ij}. \tag{1}$$

The producer-specific productivity term, z_i, is assumed to be drawn from a Fréchet probability distribution, $z_i \sim F_i(z) = e^{-T_i z^{-\theta}}$. Here, $T_i > 0$ is a producer-specific parameter that governs a region's productivity outcome, so as T_i grows larger, the probability of drawing a large value for the idiosyncratic efficiency outcome z_i increases. We refer to T_i as agricultural capacity. The parameter $\theta > 1$ is common across producers and governs the dispersion of the productivity draws of individual producers. As θ tends to infinity, the probability of any individual region maintaining a large comparative advantage decreases (i.e., large θ values imply that productivity differences between regions will be minimal and differences in regions' comparative advantages will therefore be small). The employment of the Fréchet distribution is a realistic approach since its quality of focusing on extreme values captures both individual producers' productivity and the overall distribution of comparative advantages across all producers.

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[4] A vast existing literature analyzes the heterogeneity of farmers' responses to weather and climate conditions. Starting with their canonical Ricardian approach, Mendelsohn, Nordhaus and Shaw (1994) forecast that climate change will create winners and losers in U.S. agriculture depending on the best use of farmers' land. Cai and Dall'erba (2021) offer a review and a test of the more recent contributions that add heterogeneous producers' resilience to weather shocks depending on geographical location.

[5] Bilateral trade costs are modeled in a multiplicative ("iceberg") fashion and assuming that there are no intra-region trade costs (i.e., $t_{ii} = 1$).

In turn, we consider food processing plants and other intermediate users of crops as the demand side (as final household demand comprises a comparatively small share of primary crops' use in the United States). We index these intermediate users by j, and we refer to them as importers, consumers and the destination of the commodity interchangeably. Consumers utilize farmers' crops according to a CES technology depicted in Equation (2):

$$Q_j(l) = \left[\int_0^1 Q_i(l)^{\frac{-(1-\sigma)}{\sigma}} \, dl \right]^{\frac{-\sigma}{(1-\sigma)}}, \tag{2}$$

where $\sigma > 0$ is the elasticity of substitution, and $Q_j(l)$ denotes the quantity of good l consumed by j from source i. For simplicity of notation, we omit l from the rest of the description of the model.

Next, the Fréchet distribution, Equation (1), and Equation (2) are combined to retrieve a distribution of final prices: $G_j(p) = 1 - e^{-\Phi_j p^\theta}$. Here, $\Phi_j = \sum_i^I T_i (c_i t_{ij})^{-\theta}$, where I denotes the set of all producers, ultimately connects all regions' technologies, production costs and bilateral trade costs into the final price faced by purchaser j. This relationship is illustrated in Equation (3):

$$p_j = \gamma \left[\sum_i^I T_i (c_i t_{ij})^{-\theta} \right]^{-\frac{1}{\theta}}, \tag{3}$$

where $\gamma = \Gamma \left(\frac{\theta + 1 - \sigma}{\theta} \right)$ and Γ is the gamma function. The model thus captures a market where each profit-maximizing producer offers a different price to each expenditure-minimizing consumer determined by the producer's technology/productivity parameter T_i in conjunction with unit production costs c_i and trade costs t_{ij}. In turn, the intermediate user possessing the production technology expressed by Equation (2) sees all prices and chooses the lowest one. Therefore, the allocation of commodities reached by the producers and consumers yields the market equilibrium illustrated in Equation (3).

To empirically consider equilibrium deviations and their welfare consequences, the structural parameters T_i, θ, and t_{ij} are connected with information on production, consumption, and bilateral trade between regions. Let $X_j = \sum_i^I X_{ij}$ be region j's expenditures on commodities from all regions, where X_{ij} is the value of trade going from i to j (including j's purchases from itself). The distribution of prices introduced earlier implies that the fraction of a state's expenditure on crops from any state i is equal to the probability that the state i offers the lowest price. Thus, trade shares are connected to the structural parameters as seen in Equation (4):

$$\frac{X_{ij}}{X_j} = \frac{T_i(c_i t_{ij})^{-\theta}}{\sum_i^I T_i(c_i t_{ij})^{-\theta}}. \tag{4}$$

Equation (4) has two empirical properties regarding short-run substitution behavior in the face of extreme weather events[6]. By simulating a region's decline in crop yields through a reduction in the value of T_k, Equation (4) implies that if a region is impacted by some adverse shock to its production (for instance, adverse weather conditions during the growing season), the region will be obliged to rely more on imports. On the other hand, if the shock to production affects instead any of the region's import sources, then the region will import less from the affected producer[7].

Because crop production combines several inputs, we assume that harvesting a given land area utilizes the operating inputs labor and land together with intermediate inputs (e.g., seed and fertilizer) based on a Cobb-Douglas function:

$$c_i = (w_i^\alpha r_i^{1-\alpha})^\beta p_i^{1-\beta} = \lambda_i^\beta p_i^{1-\beta}, \tag{5}$$

where w_i is the wage rate, r_i is the land rental rate, α is the share of operating expenses from labor and land inputs (denoted λ_i), and β is the labor and land share of production costs. p_i reflects the price index for intermediate inputs, which comprise a share of production costs equal to $1-\beta$. We additionally normalize Equation (4) by multiplying it by domestic sales, $\left(\frac{X_j}{X_{jj}}\right)$, and thus obtain Equation (6). A final step that allows for relative prices to be eliminated from the model (and therefore for regions' consumption shares to thus be expressed as a function of operating expenses, fundamental productivity levels, and trade costs) involves combining the expression for intermediate use with Equation (3) into Equation (6):

$$\frac{X_{ij}}{X_{jj}} = \frac{T_i}{T_j}\left(\frac{\lambda_i}{\lambda_j}\right)^{-\theta\beta}\left(\frac{p_i}{p_j}\right)^{-\theta(1-\beta)} t_{ij}^{-\theta}, \tag{6}$$

which thereby generates the trade-share equation which will be the relationship of primary interest:

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[6] Let $\pi_{ij} = X_{ij}/X_j$. Then $\partial\pi_{ij}/\partial T_j < 0$, i.e., there is an inverse relationship between region j's expenditures on goods from producing region i and the level of j's agricultural capacity. Further $\partial\pi_{ij}/\partial T_i > 0$, i.e. there is a positive relationship between region j's expenditure on goods from producing region i and the level of i's own agricultural capacity.

[7] Dall'erba, Chen and Nava (2021) provide empirical evidence of producers substituting domestic intermediate inputs for imports when U.S. states are impacted by drought events.

$$\frac{X'_{ij}}{X'_{jj}} = \left(\frac{T_i^{\frac{1}{\beta}}}{\lambda_i^{\theta}}\right)\left(\frac{\lambda_j^{\theta}}{T_j^{\frac{1}{\beta}}}\right)t_{ij}^{-\theta}, \tag{7}$$

where the logarithm of the left-hand side is given by $\ln X'_{ij} = \ln X_{ij} - \left[\frac{(1-\beta)}{\beta}\right]\ln\left(\frac{X_i}{X_{ii}}\right)$ and $\ln X'_{jj} = \ln X_{jj} - \left[\frac{(1-\beta)}{\beta}\right]\ln\left(\frac{X_j}{X_{jj}}\right)$, which is defined as normalized trade.

Equation (7) is a version of the gravity equation expressed in terms of expenditure shares rather than absolute trade volumes, in which the expressions in parentheses are the size terms[8]. In contrast to gravity equations derived from the demand side, normalized trade depends primarily on the regions' comparative advantages arising from differences in cost-adjusted productivity levels. For example, the size term associated with the exporter increases as the exporting region becomes more productive (i.e., T_i increases), but decreases as the exporting region's production expenses rise (i.e., λ_i increases). The technology-expense relationship is inverted for the importer. The more expensive it is for an importer to produce due to high inputs prices (i.e., λ_j increases), the more the region is likely to rely on imported consumption. In contrast, the more productive a destination region becomes (i.e., T_j increases), the greater is the region's reliance on domestic production.

Having established the relationship characterizing the determinants of bilateral trade, we can define our welfare measure as changes in consumers' real expenditure on crops. First, each region's aggregate expenditures can be obtained as $Y_i = c_i L_i$, where L_i is the number of harvested acres in i. Thus, Equation (4) can be manipulated to analyze a region's income through Equation (8):

$$c_i L_i = \sum_J \frac{T_i(c_i t_{ij})^{-\theta}}{\sum_K T_k(c_k t_{kj})^{-\theta}} X_j. \tag{8}$$

Using hat-algebra, which allows us to specify the model in terms of changes from the equilibrium (Dekle, Eaton and Kortum, 2007), we define a measure of changes in regions' equilibrium expenditures that arise from changes in the structural elements such as production costs (c_i), fundamental productivity (T_i) and trade costs (t_{ij}) as given in Equation (9):

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[8] A further re-arrangement of the equation's components allows us to define w_i^{θ} and $T_j^{1/\beta}$ as multilateral resistance terms (as discussed in Anderson and van Wincoop (2003) and others) that inhibit trade between the two regions.

$$Y_i \hat{c}_i = \hat{T}_i \hat{c}_i^{-\theta} \sum_J \frac{\hat{t}_{ij}^{-\theta} \pi_{ij}}{\sum_K \pi_{kj} \hat{T}_k \hat{c}_k^{-\theta}} \hat{X}_J, \tag{9}$$

where the hat notation describes relative changes in a variable's value. Thus, $\hat{c}_i = \frac{c_i'}{c_i}$ is the change in farmers' operating expenses per harvested acre, $\hat{T}_i = \frac{T_i'}{T_i}$ is the change in agricultural capacity, and $\hat{X}_J$ is the change in expenditure. $\pi_{ij} = \frac{X_{ij}}{X_j}$ is a bilateral trade/expenditure share that indicates how much of j's expenditure comes from i in the baseline equilibrium. Changes in trade costs are expressed as $\hat{t}_{ij}^{-\theta} = e^\tau$, where $\tau = 0$ if no change in bilateral trade costs is analyzed.

Finally, we define consumers' change in nominal expenditure in state i as $\hat{X}_i = \frac{Y_i \hat{c}_i + D_i}{X_i}$, where D_i is an additive component to account for trade imbalances (since we assume, as in EK, that trade is balanced). Then, nominal expenditure change is normalized by change in prices: $\hat{P}_i = \left[\sum_k \pi_{ki} \hat{T}_k \hat{c}_k^{-\theta} \right]^{-1/\theta}$ in order to express welfare impacts under various counterfactuals in terms of changes in real expenditures. Therefore, Equation (9) is reduced into our final expression for welfare given by Equation (10), where $\widehat{W}_i$ is the change of welfare in i:[9]

$$\widehat{W}_i = \frac{\hat{X}_i}{\hat{P}_i}. \tag{10}$$

The welfare impacts of disruptions that affect farmers' production can be studied by solving the previous system of equations with simulated values for $\hat{T}$. Similarly, we can study perturbations to bilateral trade costs, such as those caused by disruptions in the food supply chains between states, with simulated values for $\hat{t}_{ij}^{-\theta}$ [10].

3. Empirical Strategy

In this section, we first discuss the databases and the data treatment employed in our analysis. We then use these data to recover the necessary structural parameters to conduct our simulations in a two-step approach. The final sub-section describes the implied relative comparative advantages of U.S. states in the domestic market for crops.

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[9] Because our welfare measures are defined in terms of changes in real expenditures, welfare measures can be comparable across U.S. states. The theoretical model of EK models regions as representative consumers, which can be thought of as the average consumer in each region. In that sense, the average consumer in a U.S. state can be compared with that of another state.

[10] The system of equations described here can be easily solved using the tools provided in Baier, Yotov, and Zylkin (2019) and the Stata statistical software.

3.1 Data

U.S. crop markets are comprised of multiple producers with heterogeneous production technologies, but there are only three major consumers of U.S. crops: food processors and other intermediate users that buy crops for processing, exporters that resell U.S. domestic production overseas, and households that buy unprocessed crops such as fruits and vegetables. This distinction has empirical implications, as substitution effects (i.e., σ in Equation (2)) are likely to be different depending on the type of demand. For example, exporters' demand for domestic crops is determined by international consumers, while food processing plants' demand for domestic crops is an intermediate step in the mainly domestic food supply chain.

To homogenize consumption and to account for the substitution effects between crops varying across different domestic purchaser groups, we drop foreign trade from our analysis. One concern that might arise is that such a restriction limits the comprehensiveness of our analysis of crop production. We study whether our modelling decision is a limitation using our main dataset, the U.S. Freight Analysis Framework (FAF4). FAF4 contains aggregates of crops as classified by the Standard Classification of Transported Goods (SCTG), based on national-level input-output relationships. SCTG 02 refers to the crop aggregation comprising cereals and grains, while SCTG 03 encompasses fruits, vegetables, oilseeds such as soybeans, and a handful of other assorted primary food crops. The share of U.S. crop production that is exported is roughly 10% with the largest part being SCTG 02. In addition, our conceptual mathematical model developed in the previous section characterizes food processing plants as the main consumer of farmers' crops. Only 12% of U.S. crop production goes directly to households, and therefore the large majority of primary U.S. crop production goes to domestic intermediate uses.

The Bureau of Transportation Statistics (BTS) and the Federal Highway Administration (FHWA) developed the FAF4 data in an effort to impute domestic data flows between all U.S. states (including intra-state flows, i.e., states' trade with themselves) for several commodities and is based on the BTS Commodity Flow Survey (CFS) for most types of commodities; however, because the CFS treats goods transported by agricultural firms as outside of its scope, the FAF4 dataset uses information from the U.S. Department of Agriculture's Census of Agriculture to more accurately model the true extent of domestic trade flows in farm products. Our measure of crop trade flows is constructed by aggregating SCTG 02 (cereal crops) and SCTG 03 (fruits and

vegetables, and a handful of other crops such as soybeans). We confine our focus to the lower 48 U.S. states, as Alaska and Hawaii are not large agricultural producers and face a significantly different trading environment relative to contiguous U.S. states.

Table 1 describes the data for each of the variables used in our analysis. The top part of the table describes dyadic variables that capture attributes about the relationship between two states. Here, we consider geographical distance and whether two states share a contiguous border, two standard measures of geography-based trade costs from the gravity literature (Larch and Yotov, 2016). To measure the distance between any two states (in kilometers), we calculate the distance between the states' centroid in a shapefile using the Geoda software. The bottom part of the table describes monadic variables that capture attributes specific to individual states that will be used to estimate the comparative advantage dispersion parameter θ. Imports and exports are created using FAF4 data to describe trade flows. Both measures are in millions of 2017 U.S. dollars. Population density, which we will use as an exogenous predictor of operating costs in an instrumental variable analysis below, is collected from the 2010 U.S. Census Bureau of Statistics and is measured in population per square kilometer. Operating expenses per harvested acre are obtained from the 2017 U.S. Census of Agriculture and are measured in 2017 dollars. Climate variables that affect agricultural output during the Summer are precipitation and temperature during summer. Precipitation is measured in cubic centimeters, and temperature is measured in degrees Celsius. Weather data are collected from the Parameter-elevation Regression on Independent Slopes Model (PRISM) data base over the 20 years period between 1997 and 2017. Then, weather data are transformed into climate by taking the average of each variable over time for each location (PRISM, 2011).

Because virtually all agricultural activity occurs outside cities and our climate variables described earlier could be influenced by urbanization, we follow a two-step aggregation of our data variables. First, all data are obtained at the county level for all counties in the contiguous United States. Next, metropolitan and highly populated counties are dropped (Dall'Erba and Dominguez, 2016)[11]. Finally, we calculate state averages excluding metropolitan and high population counties. This aggregation technique allows us to reduce weight from highly populated, urbanized regions with little agricultural production.

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[11] We define the population density cutoff at the county level is 1,600 persons per square mile.

Table 1: Trade, crop operating expenses, population density and climate variables in 2017

Dyadic Variables	Mean	S.D.	Min	Max
Distance	1827.27	1295.40	0.00	5179.18
Contiguity	0.10	0.29	0.00	1.00
Monadic Variables	**Mean**	**S.D.**	**Min**	**Max**
Imports	9,280.78	9,934.75	233.99	43,387.97
Exports	9,280.78	10,927.41	105.50	46,177.39
Operating expenses per harvested acre	708.75	492.77	75.83	2478.09
Population density	83.85	61.69	6.46	286.11
Summer temperature	24.25	3.70	18.27	32.30
Summer precipitation	42.27	16.68	3.33	82.93

Notes: The number of observations for our dyadic variables is 2,304, while the number of observations for our monadic variables is 48. All monetary measures are in 2017 U.S. dollars. The value of imports and exports are created using FAF4. Distance is measured in kilometers. Population density is measured in population per square kilometers. Precipitation is measured in cubic centimeters, and temperature is measured in degrees Celsius.

3.2 Recovering Structural Parameters

Recovering the structural parameters θ and T_i requires a two-step approach. First, Equation (7) is parameterized with the log-linearization of the expression. Equation (12) is the regression model, where the size terms are denoted by S_i for the exporter and S_j for the importer and are captured through the use of importer and exporter fixed effects. The error term is ϵ_{ij}. Then, size term estimates are used in a second-step as the dependent variable in the estimation of Equation (13), where the size terms come from Equation (7) and are denoted as $\widehat{S}_i$ and $\widehat{S}_j$ for the exporter and the importer respectively:

$$\ln \frac{x'_{ij}}{x'_{jj}} = -\theta \ln t_{ij} + S_i - S_j + \epsilon_{ij}, \tag{12}$$

$$\widehat{S}_k = \alpha + \frac{1}{\beta} \ln T_k - \theta \ln \lambda_k + \nu_k, \tag{13}$$

where ν_k is the error term. In contrast with Equation (12), in which θ is attached to a variable (t_{ij}) that is difficult to directly measure empirically, θ can be recovered from Equation (13) since it is associated with an observable variable $(\lambda_k,$ or operating expenses). We assign a value of 0.12 to the share of intermediate inputs $(1 - \beta)$ based on input-output data from IMPLAN[12]. The

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[12] We consider $1 - \beta = 0.12$, the weighted average of intermediate-input shares in our crop aggregations for SCTG02 and SCTG03 (for example, fruits and vegetables), acknowledging that some crops in our aggregation require higher operating expenses because of differences in labor and/or land intensity in production. For robustness, we consider the impact of alternative assumptions on β for our simulation results, and find that values in the range $1 - \beta \in [0.08, 0.21]$ generate qualitatively similar results in our counterfactual simulations.

estimation of Equation (12) is carried out through the use of dummy variables. Since bilateral trade costs are not readily observable, we approximate them through the use of two variables reflecting geographical determinants of trade costs: a contiguity dummy that indicates whether two states share the same border and six dummies corresponding to the distance bins (0, 865], (865, 1730], (1730, 2595], (2595, 3460], (3460, 4325] and (4325, Max][13]. Since we assume that intra-trade has zero cost (i.e., $t_{ii} = 1$), then all dummies for distance are interpreted relative to intra-trade costs. Importer and exporter fixed effect dummy variables are included, but normalized to sum to zero. Notice that the estimation of Equation (12) will drop all zero-trade observations (i.e., $X_{ij} = 0$). Because trade between regions is not symmetric, the variance-covariance matrix is assumed to have diagonal elements $\sigma_1^2 + \sigma_2^2$ that affect both two-way trade and one-way trade, and certain nonzero off-diagonal elements σ_2^2 that affect only two-way trade. For this reason, we estimate Equation (12) by feasible generalized least squares[14] (FGLS).

Figure 1 reports estimates from Equation (12). In panel (a), we report the proxy estimates for bilateral trade costs (using trade data aggregated across the two SCTG commodity groupings). As expected, two states sharing a contiguous border tends to be associated with more trade between the states. Our results indicate also that trade volumes decrease with distance, but the marginal impact of distance on trade becomes attenuated in the last two distance bins. We attribute this to freight mode decisions. Our FAF4 data shows that while most crops are shipped within short distances by truck, the volume shipped by truck decreases with distance but increases for rail and barges, modes for which long distances incur only small marginal transportation costs.

In panel (b), estimates of the fixed effects are depicted graphically. The estimates associated with the size terms are structurally symmetric as shown in Equation (7). Deviations from symmetry represent non-market influences that affect either the imports or exports from a region. For instance, as described earlier, each set of fixed effects can be interpreted as either competitiveness or openness for the exporter and importer side respectively. In an international trade context, this distinction typically reflects institutional and policy differences that affect

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[13] Using distance bins, as supposed to a continuous distance measure, allows us to assign no ad-hoc parametrization to Equation (12). No significant difference is found when using a continuous measure of distance when running Equation (13).

[14] Recent papers that estimate Equation (12) report employing versions of the Poisson pseudo-maximum likelihood (PPML) estimator to address the heteroskedasticity and zero-trade issues. In our two-step estimation to estimate θ, we do not advise the employment of PPML since the second step, Equation (13), is a linear estimator.

specific countries, such as weak government institutions, which impact exports, and policies that encourage citizens to consume domestically sourced goods, which affect imports. We test for symmetry of the fixed effect estimates by testing the difference between each pair of estimates. Furthermore, the imposed symmetry of our structural model prevents us from testing whether point estimates are statistically different from zero since each set of size-term fixed effects crosses zero. For this reason, the symmetry test also serves as a significance test. The point estimates are shown without confidence intervals, but the confidence interval corresponding to the test of whether each pair is equal to each other is shown.

Figure 1: Estimation results from gravity equation: Distance and importer- and exporter-size effects.
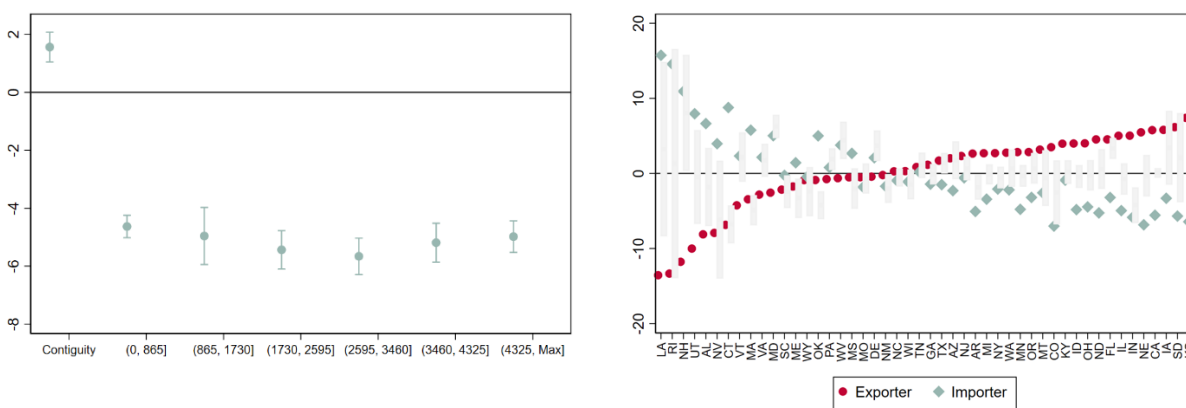
(a) Bilateral trade costs   (b) Size terms

Note: R^2 is 0.97 with 1,334 observations. The imposed symmetry of our structural model prevents us from testing whether point estimates are statistically different from zero since each set of size term fixed effects crosses zero. For this reason, we instead test whether the absolute values of point estimates in each pair of size terms is equal to each other. The point estimates are shown without confidence intervals, but the confidence interval for the test of whether each pair is equal to each other is shown.

Using estimates for the size terms, we estimate Equation (13) to recover θ. Since agricultural capacity (T_k) is not observed, we proxy it using historical precipitation and temperature for each U.S. state, following a quadratic polynomial with an interaction term. Because we expect high operating expenses per acre to be associated with high levels of agricultural capacity (e.g., high operating expenses might be indicative of a region having more productive soil, and thus higher levels of demand for inputs), we employ the two-stage least squares (2SLS) estimator. Our instrumental variable is average population density in rural counties within each U.S. state. We expect that the wage component in Equation (5) is affected by

population density, so our use of this variable ensures that our instrument affects operating expenses per acre, but not other determinants of agricultural capacity such as climate[15].

Table 2 reports the results from the estimation of Equation (13). The exporter columns use the size terms related to the exporter, and the importer columns use the size terms related to the importer. The first column employs the OLS estimator and the second column the 2SLS estimator. The variance inflation factors of the climate variables are above 100 in every regression, so the climate estimates are highly correlated[16]. Our conceptual framework predicts θ to be positive and greater than 1, so the coefficient associated with operating expenses per harvested acre must be negative and less than 1. The results from the OLS estimations show that θ is not statistically different from zero. As expected, correcting for endogeneity leads to larger and statistically significant estimates of θ, which again reflects the notion that unobserved aspects of productivity might be correlated with operating expenses. The specification based on the exporter size terms yield an estimate $\theta = 2.962$, while the estimates obtained by using the importer size terms generate a slightly larger value of $\theta = 3.804$. Table 2 also reports the first stage and allows us to reject the hypothesis that our instrument is weak[17].

We compare our estimates of the comparative advantage dispersion parameter with those of Reimer and Li (2010) who estimate this parameter for crop yields at the international level. Their point estimates for θ are no lower than 2.52 and no higher than 4.96. Using a generalized method of moments approach, they estimate $\theta = 2.83$ compared to a value of $\theta = 2.52$ using maximum likelihood and a parametrization of the Fréchet distribution. The authors also report a larger estimate of θ at 4.96 based on using the relative prices of the commodities under consideration to proxy for elements of the EK model. However, Simonovska and Waugh (2014) show that the use of such proxies can systematically generate overestimates θ. Therefore, because our importer side

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[15] The threat to the exclusion restriction when population density is the aggregate of the whole state is that climate change is affected by activities related to population density such as traffic and polluting industries, which are typically concentrated in cities and their surrounding areas. Our instrument is weakly and negatively correlated with temperature in the growing season. In fact, a large part of the variation in agricultural productivity is explained by climate and land characteristics, ensuring that population density only affects operating expenses per harvested acre (Liang et al., 2017).

[16] Because the coefficient of interest is θ, climate proxies are simply used as control variables.

[17] A concern associated with the estimations in Table 2 is the finite sample properties of the IV estimator (Heid, Larch, and Yotov, 2017). Andrews and Armstrong (2017) report that exactly identified models with low number of observations often possess undesirable properties (such that the IV estimator is consistent but not unbiased), but the authors propose an estimator that is unbiased. We implement their estimator and find no difference with the estimations in Table 2.

Table 2: Second step estimations, using OLS and 2SLS estimators

	Exporter		Importer	
	OLS	2SLS	OLS	2SLS
Labor expenses	−0.008	−2.962**	−0.497	−3.804***
	(1.138)	(1.344)	(1.175)	(1.399)
Temperature	2.643	2.301	3.433	3.049
	(2.899)	(2.968)	(2.995)	(1.399)
Precipitation	−0.167	−0.032	−0.136	0.015
	(0.325)	(0.313)	(0.336)	(0.315)
Temperature^2	−0.056	−0.044	−0.068	−0.055
	(0.058)	(0.054)	(0.059)	(0.054)
Precipitation^2	−0.001	0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Interaction	0.007	−0.001	0.002	−0.008
	(0.015)	(0.018)	(0.016)	(0.018)
Constant	−29.864	−10.245	−36.514	−14.545
	(37.515)	(37.750)	(38.748)	(37.9423)
		First Stage		
Population Density		0.709***		0.709***
		(0.085)		(0.085)
F Statistic		14.81		14.81
R^2	0.10	0.59	0.08	0.59
Observations	48	48	48	48

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Operating expenses and population density are natural logarithm values. Coefficient associated with operating expenses is θ. Values in parentheses are robust standard errors. Coefficients for climate variables are recovered up to the constant $\frac{1}{\beta}$.

estimate of $\theta = 2.962$ falls squarely in the range of estimates found by Reimer and Li (2010), we choose it as our preferred value for the comparative advantage dispersion parameter because it closely approximates existing values of this parameter from the literature.

3.3 Comparative Advantage

To analyze the comparative advantage of each U.S. state, Equation (13) is re-arranged into the relationship $\widehat{T}_i = \left(e^{\widehat{S}_i}\lambda_i^\theta\right)^\beta$, which expresses agricultural capacity as a function of parameters, the estimated size terms, and operating expenses. Using data on operating expenses per harvested acre, the estimates for the exporters' size term, our preferred value for $\theta = 2.962$, and $\beta = 0.88$, we calculate the value of each state's agricultural capacity. Thus, each state's exporter size terms can

be decomposed into an agricultural capacity component and an operating expense component. This decomposition is shown in Figure 3.

Figure 2: Comparative advantage (exporter size-term) decomposition

Note: Figure reports size terms estimates obtained using Equation (13): natural log of the implied level of agricultural capacity and natural log of operating expenses per harvested acre in each U.S. state multiplied by $\theta = 2.962.$ Implied level of agricultural capacity is calculated as $\hat{T}_i = \left(e^{\hat{S}_i}\lambda_i^{\theta}\right)^{\beta}$.

All else constant, Equation (7) implies that net exporters have high levels of agricultural capacity relative to their operating expenses $\left(T_i^{1/\beta} > \lambda_i^{\theta}\right)$. This is because regions with relatively high levels of agricultural capacity relative to their input costs are better able to specialize in crop production. Similarly, net importers have low levels of agricultural capacity relative to their operating expenses $(T_i^{1/\beta} < \lambda_i^{\theta})$. Therefore, the size term can be interpreted as a state's comparative advantage. Figure 3 shows that a state's comparative advantage largely depends on its agricultural capacity. While operating expenses per harvested acre typically fall within a relatively narrow range of values, agricultural capacity can take extreme values. Further, as implied by the model, states with high agricultural capacity relative to operating expenses are predicted to be net exporters based on comparative advantages maintained over other states.

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Our results indicate that Kansas, South Dakota, Iowa, California, Nebraska, Indiana, Illinois and Florida have a comparative advantage in the U.S. market for crops. Not surprisingly, these eight states jointly account for over half of all U.S. domestic crop production. However, comparative advantage in crop production is not only determined by agricultural capacity. Agricultural capacity is largest for California and Florida, but their comparative advantage is dragged down by high operating expenses within the state. This emphasizes the importance of reducing operating expenses to compete. On the other hand, Louisiana, Rhode Island, New Hampshire, Utah, Alabama and Nevada have the lowest levels of agricultural capacity and high operating expenses. These six states export less than 2% of domestic crop production and import up to four times what they export.

4. Food vulnerability simulation results

We next turn to employing the estimated structural parameters that reflect the states' comparative advantages and our data on domestic crop trade to conduct two counterfactual simulations. The first simulation is designed to assess the U.S. states' vulnerability to food supply chain disruptions. This scenario considers an increase in bilateral trade costs separately (i.e. $t_{ij} = 1.5 \ \forall j \neq i$) for each state to quantify the degree to which individual states are vulnerable to food supply disruptions. While the state's comparative advantage can help mitigate welfare losses caused by supply chain disruptions, we conduct an additional simulation to investigate the ability of the existing food supply chain to mitigate welfare losses from events that affect each state's ability to produce crops (i.e., $T_i = 0.5 \ \forall i$). The numerical results on the key outcomes for each of our simulations are shown in Table 3 and further describe in Figure 3 and Figure 4. Notice that we decompose our welfare measure into a total expenditure term, $\widehat{X}_\iota$, and a price index term, $\widehat{P}_\iota$, so our welfare measure is real expenditure for crops (Arkolakis, Costinot, and Rodríguez-Clare, 2012).

On average, both simulations produce welfare losses around 15%, but divergence in counterfactual expenditure and prices signals the mechanisms that govern each simulated event. Our supply chain shock results indicate that expenditure fall by 16% with a small hike in the level of prices. The latter effect suggests that the primary factor governing welfare losses from disruption of supply chains in the U.S. is shortage of crops. Recent literature (Ferguson and Gars, 2020; Dall'Erba, Chen, and Nava, 2021) provide empirical evidence of producers substituting domestic intermediate inputs for imports when U.S. states are impacted by drought events. Results in the bottom part of Table 3 investigate the capacity for states to mitigate impacts of adverse production shocks through trade. In contrast to our initial simulation, our production shock

<div align="center">Table 3: Simulation results</div>

	Mean	Std. dev	Minimum	Maximum
Supply chain shock				
$\widehat{W}_\iota$	0.82	0.072	0.66	0.96
$\widehat{X}_\iota$	0.84	0.069	0.67	0.96
$\widehat{P}_\iota$	1.02	0.010	1.01	1.05
Production shock				
$\widehat{W}_\iota$	0.89	0.081	0.71	0.99
$\widehat{X}_\iota$	1.12	0.038	1.04	1.19
$\widehat{P}_\iota$	1.27	0.107	1.07	1.45

Notes: Table shows descriptive statistics from simulation results for all U.S. states. Supply chain disruptions and production shocks are calculated with Equation (10).

counterfactual increases both the level of expenditure and crop prices. Our results highlight that states are able to substitute local production shortfalls by sourcing crops from other states at relatively expensive prices. Nevertheless, the capacity of states to cope with each simulated shock differs and so their extent to which expenditure and prices changes. Table 3 shows that U.S. states are largely heterogenous in their responses to the adverse events with some states being virtually unaffected by either shock. In Figure 3 and Figure 4 we investigate further our simulation results including states competitiveness (Figure 2) as an additional dimension in our analysis.

In Figure 3, we plot our results from Table 3 by comparing welfare and the level of competitiveness (see discussion in section 3.3) of each state (top panel), and prices and the level expenditure (bottom). Comparison between the level of states' competitiveness and their welfare losses shows that large agricultural producers (rightmost part of Figure 2) are the least impacted by supply chain disruptions, while small agricultural states (leftmost part of Figure 2) are the most

Figure 3: Supply chain disruption simulation results
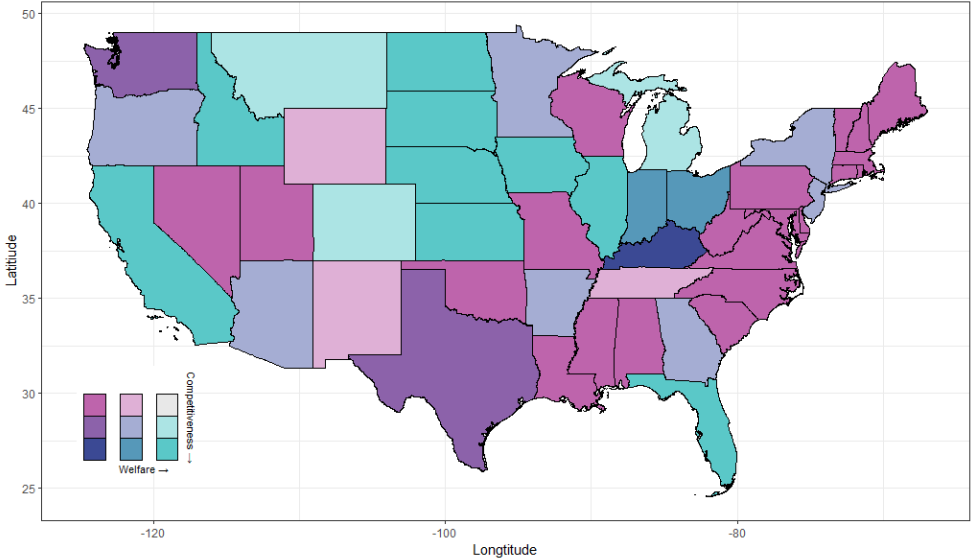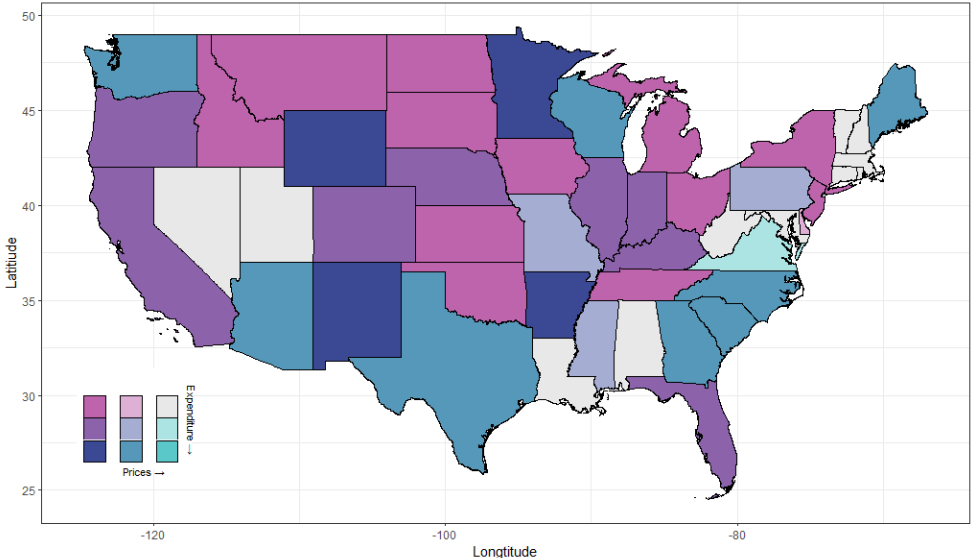
(a) Welfare and Competitiveness
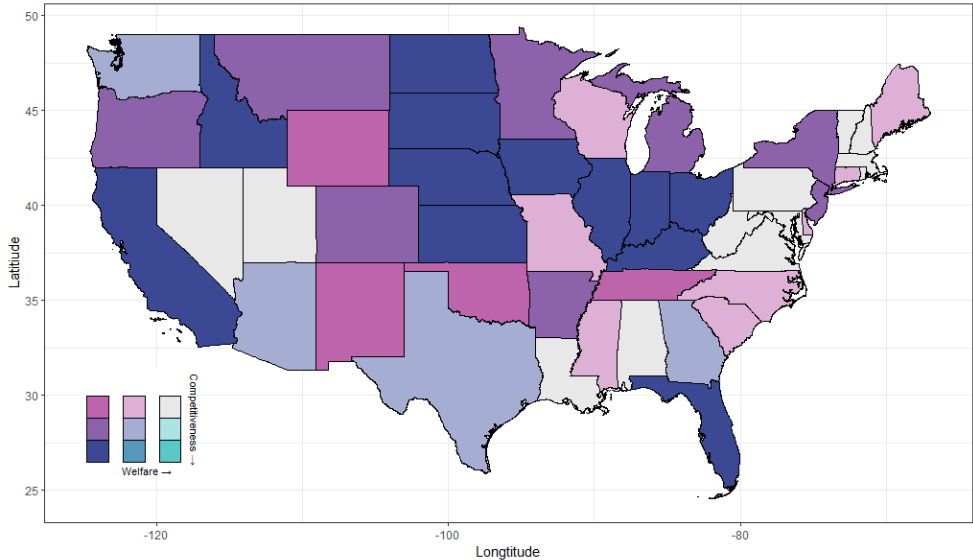

(b) Price and Expenditure

Note: Figures describe our welfare results compared with each state's competitiveness (top), and the level of prices and expenditure (bottom) in the simulation described in Table 3.

impacted. The latter observations suggests that the extent to which states substitute imports for domestic production depends on their initial level of agricultural capacity. To illustrate, food producers in big agricultural states such as California, Florida, and Illinois experience welfare losses of less than 5%, mostly being affected by slight reductions in the availability of crops per the bottom panel. On the other hand, producers in Alabama, Louisiana and Nevada experience welfare losses close to 30%, and the bottom panel show that most of the effect come from a reduction in the level of expenditure on crops.

An initial implication of our results in Figure 3 is the role of proximity to crop sources to ameliorate the impacts of supply disruptions on food processors' production. The role of proximity as a determinant in the location where crop users decide to establish their operations has long been investigated (Henderson, and McNamara, 2000; Jakubicek, Woudsma, 2013; Li, Miao, and Khana, 2019), but its advocacy as a mitigating factor is a recent topic of debate (Hobbs, 2020; Thilmany et al., 2020; Martinez, Maples, and Benavidez, 2021). An opposing argument is the role of inter-state trade to cope with agricultural productions shocks such as those coming from droughts and floods. Ferguson and Gars (2020) find that crop producers substitute domestic inputs for imports after they experience a drought event, and Dall'Erba, Chen, and Nava (2021) calculate that inter-state trade will serve as a $14.5 billion mitigation tool for farmers in the U.S. to deal with future weather conditions. In Figure 4, we expand the conclusions of Dall'Erba, Chen, and Nava (2021) to study the mechanisms that govern their conclusions.

Similar to Figure 3, Figure 4 plots our results from Table 3 by comparing welfare and the level of competitiveness (see discussion in section 3.3) of each state (top panel), and prices and the level expenditure (bottom). For our production shock simulation, we expect the largest losses to be associated with the states with the highest comparative advantage; but by limiting our focus to the states with the highest comparative advantage (rightmost states in Figure 2), we can study the role of the existing food supply chain on substituting domestic consumption for imports. Our results suggest that the initial level of imports is a major factor driving the welfare results of our simulation. Intermediate users in Montana, Kansas and North Dakota rely heavily on their domestic crop production. These states experience a large change in their implied comparative advantage, but their nominal food expenditure and prices change by similar amounts. On the other hand, states with a more balance composition of imports and domestic consumption have the least

Figure 4: Production shock simulation results
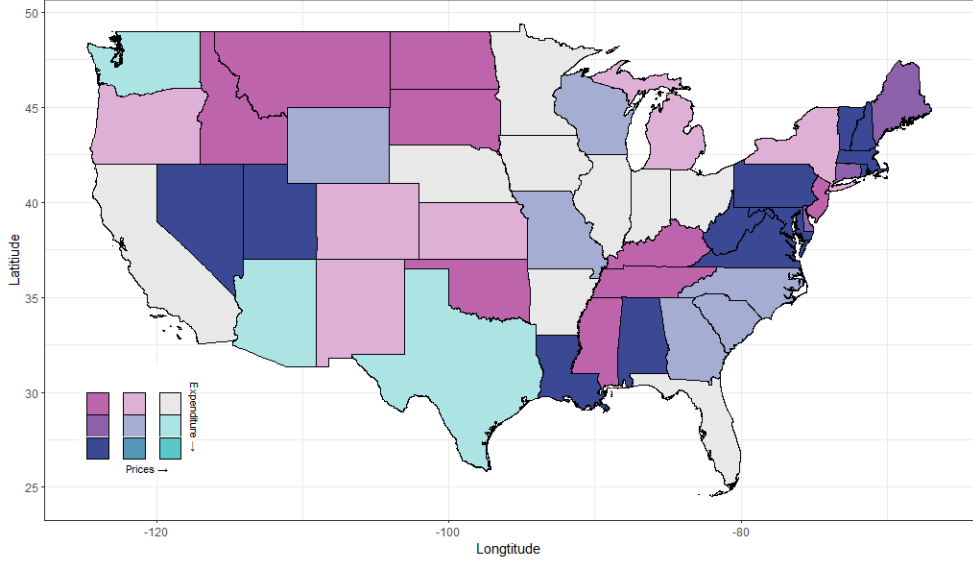
(a) Welfare and Competitiveness

(b) Price and Expenditure

Note: Figures describe our welfare results compared with each state's competitiveness (top), and the level of prices and expenditure (bottom) in the simulation described in Table 3.

severe impacts, suggesting that inter- and intra-supply chains are developed at similar levels. Substitution of domestic consumption for imports is more feasible in these states.

In summary, our three counterfactual analyses emphasize that the distributional impacts of domestic supply chain disruptions hinge on the extent of individual states' agricultural productivity capacities, and that the capacity for states to mitigate the impacts of adverse production shocks through trade relies on the degree to which states are able to substitute local production shortfalls by sourcing crops from other states.

5. Conclusions

Our extension of the Ricardian trade model of EK offers a comprehensive and structurally grounded model of the U.S. market for crops that can be employed to analyze a large array of counterfactuals concerning food security within the United States. We incorporate assumptions about the heterogeneity of farmers' production and characterize the optimizing behavior of the model's agents. Our conceptual framework also considers the realities of the U.S. domestic food system and models food processing plants as the main consumer of farmers' crops. An advantage of our approach is that we consider the production side, so our model permits an analysis of market mechanisms that govern crop trade, expenditure and prices through a specification of the U.S. states' comparative advantage. Finally, we decompose each U.S. state's comparative advantage in the market for crops into an agricultural capacity term and an operating expenses term, which can be used to study the determinants of the welfare impacts that manifest in our various counterfactual scenarios.

We implement our general equilibrium model of interstate crop trade to assess the food vulnerabilities of the existing U.S. domestic food supply chain. Our simulation results provide insights into U.S. states food vulnerabilities through food processing plants' expenditure on crops, crop prices, and overall consumer welfare. We consider two alternative counterfactual scenarios to assess the geography of the domestic food supply chain and the implications of these counterfactuals for production, consumption, and consumer (i.e., intermediate users) welfare. The first counterfactual is concerned with supply chain disruption that increases the trade costs between states. We demonstrate that states' vulnerability to disruptions in the food supply chains or production shocks can be explained by their relative comparative advantage in the domestic market for crops. We find that the distribution of welfare losses caused by disruptions in the existing supply chains depends on a state's ability to substitute imports for domestic production. We

conduct an additional simulation to investigate the ability of the existing food supply chain to mitigate welfare losses from events that affect each state's ability to produce crops, arriving to similar conclusions regardless of a state's initial comparative advantage. The policy implications of our study suggest that the resilience and efficiency of agricultural supply chains depends on both inward- and outward-oriented approaches to the design of domestic food systems, and crucially, that interdependence as facilitated by trade is a key factor in allowing regions to mitigate adverse shocks to their own production.

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