Building Resilience against Weather Shocks: Should we go Local?

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November 2, 2020

Abstract

Advances in agricultural production and specialization have allowed some U.S. states to become net food exporters, while others have become net importers. Specialization requires using farming practices that the general public perceived as unhealthy and detrimental to the environment but necessary to achieve high output levels with limited resources; so, consumers' advocacy to shift food production back to local markets is gaining momentum. However, evidence suggests that allowing markets to rely on a few food production sources posits concerns about food vulnerability to droughts and floods. Improvements in the efficiency of food supply chains that reduce the cost of trade have been proposed to mitigate welfare losses caused by extreme weather events. I analyze consumers' food expenditure under these two opposing policy recommendations. I employ a Ricardian general equilibrium model for the U.S. domestic market of crops and find that welfare gains are higher under reduced costs of trade than under improved local agricultural productivity. The divergence in gains between each policy's welfare effects is driven by the benefits to net importers of food with low levels of agricultural production. Moreover, my results indicate that U.S. resilience against weather shocks is higher under the enhanced efficiency of food supply chains than under improved local agricultural productivity. In contrast to previous studies, my Ricardian application rules out non-market factors present in international trade studies. I present evidence that the U.S. market for crops is more suitable for this type of analysis than the international setting.

Keywords: Food supply chains, climate change, extreme weather, general equilibrium, Ricardian trade.

1 Introduction

Because large crop producers employ farming practices that the general public perceived as unhealthy and detrimental to the environment, consumers' advocacy to shift food production back to local markets is gaining political momentum. Biedny et al. (2020) find that self-proclaimed Democrats' and Republicans' support for government intervention to require food supply to come from local sources has increased in the last decade. While advocates of local agriculture are interested in valid health and environmental issues, policymakers should see this trend cautiously. Increasing reliance on local markets assumes food vulnerability concerns if most of their food supply is locally grown. During the 2012 drought in California, farmworkers saw themselves unemployed and facing high prices at grocery stores (Rodriguez et al., 2015; Greene, 2018). Similarly, if regions rely on imports from a few sources, food production shocks are also transmitted into higher food prices in foreign markets (Tortajada et al., 2017). A policy that aims to promote local agriculture must consider not only health and environment but also food expenditure and resilience against weather shocks. Under this context, I evaluate a policy that improves U.S. states' local agricultural productivity in terms of consumers' welfare and improvements in the state's resilience to extreme weather events.

Recent literature studies the role of trade in shaping food security and self-reliance. Burgess and Donaldson (2010) employ rail data from the colonial era in India to show causal evidence that famines are reduced by trade. However, import dependency and the increasing complexity of food supply chains carry new challenges. Using simulations of production shocks at the international level, Puma et al. (2015) find significant import losses associated with more connected countries. Likewise, Gephart et al. (2016) employ a forward shock-propagation model, and their results suggest that the reduction of import reliance can lessen food vulnerability to production shocks. The latter two analyses of food vulnerability and trade focus on consumer behavior and food production separately. For example, Gephart et al. (2016) account for consumers' import substitution between goods, allowing the consumer to adjust her expenditure according to her tastes, but fails to account for producers' responses. Since the model does not permit producers to gain market share over those impacted by the weather shock, welfare gains in regions not affected by the weather shock are likely understated. On the other hand, Puma et al. (2015) study countries' welfare after simulating disruptions in European and Asian exports, but their simulations do not account for consumers' substitution responses, overstating welfare losses.

Furthermore, none of the previously discussed studies consider producer heterogeneity, which allows for realistic production circumstances such as various responses to weather shocks. In the U.S., a vast tradition of economics studies evidence on the heterogeneity of farmers' responses to weather events and climate change. Starting with their canonical Ricardian approach, Mendelsohn et al. (1994) forecast that climate change will create winners and losers in U.S. agriculture depending on the best use of farmers' land. Schlenker et al. (2005, 2006) incorporate space into the Ricardian approach and find heterogeneous producers' resilience to weather shocks depending on geographical characteristics. More recently, Chen et al. (2020) expand the Ricardian approach to account for trade, providing evidence of producers substituting domestic intermediate inputs for imports when impacted by drought events. Therefore, a food vulnerability analysis must consider the simultaneity of supply and demand and the heterogeneity of producers' technologies.

Simultaneous modeling of consumers' utility and producers' profit optimization problems allows to connect trade between regions with its determinants through trade (Anderson, 1979). A resulting gravity-like equation is employed to generate normative implications relevant to the researcher and her stakeholders. The form of the gravity equation, however, depends on the research interest. Anderson and Van Wincoop (2003) popularize the Armington-CES model that emphasizes demand determinants such as regions' per capita income. On the other hand, Eaton and Kortum (2002) propose a Ricardian analysis that emphasizes producers' relative comparative advantage through prices and intermediate inputs.[1] The Ricardian trade model permits producers to have a level of relative comparative advantage via efficiency parameters, so shocks in a region's efficiency

[1] Both the Armington-CES model and the Ricardian trade model are equivalent under the assumption of no intermediate inputs and the trade elasticity θ being equal to $1 - \sigma$, where σ is the elasticity of substitution between goods (Yotov et al., 2016). My application relaxes these assumptions, allowing for a more realistic modeling of U.S. agriculture.

alters the models' equilibrium and effectively creates counterfactual scenarios. Reimer and Li (2010) exploit this feature of the Ricardian trade model to study how yield variability will affect households for twenty-three countries, finding that openness to trade is positively related to welfare distributions. Building on their Ricardian application, I study the effect of two opposing policy recommendations on consumers' welfare and their resilience to weather shocks in the U.S.[2] One policy promotes local agriculture by improving local agricultural productivity, and another one enhances food supply chains between U.S. states. I find that welfare gains are 13% higher under reduced costs of trade than under improved local agricultural productivity. Moreover, my results indicate that U.S. resilience against weather shocks is higher under the enhanced efficiency of food supply chains than under improved local agricultural productivity.

My Ricardian application diverges from that of Reimer and Li (2010) in two unique ways. I employ a U.S. domestic trade data set to rule out non-market influences that govern trade flows at the international level. A limitation of using international trade data is that it hides non-market influences such as trade barriers and cultural proximity between countries (Felbermayr and Toubal, 2010; Balogh, 2015; Carrère and Masood, 2018). The domestic market of crops in the U.S. not only rules out non-market influences, but gains from trade simulation results imply that the U.S. is farther away from autarky than the international setting. A second divergence is my focus on short-run variations on efficiency that are region-specific. I exploit a different set of structural parameters to simulate local and foreign production shocks as well as the effect of each policy recommendation. Using welfare results, I construct a resilience measure to compare both opposing policy recommendations.

This paper is organized as follows. The next section reviews the formulation of Eaton and Kortum (2002). Section 3 presents my empirical strategy. First, I describe how I process the data to capture the economic realities of the U.S. domestic crop market. Then, I employ estimation techniques to recover the necessary parameters for my post-

[2] Another variation of trade gravity models I consider is similar to the Fang and Beghin (2000) application of the Heckscher-Ohlin model that emphasizes endowments as a source of comparative advantage. This model, however, does not permit for production shocks, which is the main interest of this manuscript.

estimation simulations. In section 4, I present the results of my simulations. Finally, I offer concluding remarks in section 5.

2 Ricardian trade model of U.S. crop producers

My application of the Ricardian trade model introduced by Eaton and Kortum (2002) considers the two sides of the U.S. crop domestic market. On the one hand, farmers are crop producers. I denote farmers as i and refer to them as exporters, producers and the origin of the commodity interchangeably. U.S. farmers operate under different weather, technology and land characteristics across U.S. states. I capture their heterogeneity with a regional efficiency term denoted as z_i and expenses per harvested acre denoted as c_i.[3] I denote final prices as P_{ij} and bilateral trade costs as t_{ij}, which distinguish the source of the commodity, i, and where it is consumed, j.[4] Assuming constant returns to scale technologies, final price is related to costs of production, a firm's efficiency and transportation costs as illustrated in Equation (1).

$$P_{ij} = \frac{c_i}{z_i} t_{ij} \tag{1}$$

Efficiency is assumed to be drawn from a Fréchet distribution: $F_i(z_i) = e^{-T_i z^{-\theta}}$. 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 efficiency outcome, z_i, increases. I refer to T_i as agricultural capacity. The parameter $\theta > 1$ is common across producers and influences the likelihood of few regions to have comparative advantage within the economy. As θ tends to infinity, the probability of a region having a comparative advantage decreases.[5] The employment of the Fréchet distribution is a realistic approach since it

[3]We follow the convention of Reimer and Li (2010) and identify land as the main production input. Despite our reliance on their work, we do not consider land rents as the main input cost. Ortiz-Bobea (2019) shows that under the constant returns to scale assumption, land rent reflects agricultural profits and not only input costs. For this reason, we rely on labor expenses per harvested acre.

[4]Bilateral trade costs are modeled in a multiplicative fashion. Assuming no intra-trade costs (i.e., $t_{ii} = 1$), this modelling decision implies that if region i wants region j to receive one unit of her goods, but bilateral trade costs between these two regions is $t_{ij} = 2$, then she will need to charge for the price of two units of her goods to account for freight costs as shown in Equation (1). This modeling approach is known in the literature as iceberg trade costs and represent trade costs in real terms.

[5]Assuming that climate change will increase yield variability through the increase in the probability

allows the model to incorporate comparative advantage and production heterogeneity.

In turn, crop consumers are denoted as j, and I refer to them as importers, consumers and the destination of the commodity interchangeably. A continuum of goods between zero and one is assumed. Representative consumer preferences are modeled with a constant elasticity of substitution utility function depicted in Equation (2).

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

where $\sigma > 0$ is the elasticity of substitution, U_j denotes the utility derived from the consumption of l from the source and quantity denoted as $Q_i(l)$. For ease of notation, I drop 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, $\Phi_j = \sum_I T_i(c_i t_{ij})^{-\theta}$ ultimately connects *all* regions' technologies, production costs and bilateral trade costs into the buyer's final price. This fact is illustrated in Equation (3), where $\gamma = \left[\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\right]$, and Γ is the gamma function.

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

The model is able to simulate a market where each profit maximizing producer offers a different price to each consumer based on her production technology and the cost of shipping the commodity (Equation (1)). In turn, a utility maximizing consumer with preferences expressed by Equation (2) sees all prices and chooses the lowest one. Therefore, the allocation of commodities reached by the profit maximizing behavior of the producers and the utility maximizing behavior of the consumers constitutes a market equilibrium illustrated by Equation (3).

To empirically study equilibrium deviations and their welfare consequences, the structural parameters T_i, θ and t_{ij} are connected with trade data. Let $X_j = \sum_I X_{ij}$ be expendi-

of climate shocks, Reimer and Li (2010) exploit θ to study how yield variability will affect prices and welfare across countries. In contrast to their approach, I study short run variations in efficiency that are region specific, so I instead shock the parameters T_i to simulate welfare losses such as those caused by droughts, floods and early frost.

ture on commodities from all regions, where X_{ij} is trade between i and j. The probability distribution of prices introduced earlier implies that the fraction of a state's expenditure on crops from 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 in Equation (4).

$$\frac{X_{ij}}{X_j} = \frac{T_i\,(c_i t_{ij})^{-\theta}}{\sum_K T_i (c_i t_{ij})^{-\theta}} \tag{4}$$

Equation (4) has two important properties regarding short-run substitution behavior in the face of extreme weather events. By simulating a region's decline in crop yields by reductions in T_k, Equation (4) implies that if a region is impacted by an extreme weather event, she will rely on imports. On the other hand, if the extreme weather event hits instead any of her importer partners, then she will import less from the affected state.[6] [7] Both responses are consistent with a consumer substituting from one source to another as depicted in Equation (2).

Because crop production combines several inputs, I assume that a harvested acre combines labor and intermediate inputs such as energy, agricultural chemicals and seeds with labor comprising a constant share of β such that $c_i = w_i^{\beta} p_i^{1-\beta}$. Here, w_i is labor expenses per harvested acre and p_i is defined by Equation (3) and illustrates that farmers buy inputs from other farms. In addition, I normalize Equation (4) by multiplying it by domestic sales, $(\frac{X_j}{X_{jj}})$, thus obtaining Equation (5). A final step that allows for relative prices to be eliminated from the model is combining intermediates with Equation (3) into Equation (6).

$$\frac{X_{ij}}{X_{jj}} = \frac{T_i}{T_j}\left(\frac{w_i}{w_j}\right)^{-\theta\beta}\left(\frac{p_i}{p_j}\right)^{-\theta(1-\beta)} t_{ij}^{-\theta} \tag{5}$$

$$\frac{X'_{ij}}{X'_{jj}} = \left(\frac{T_i^{\frac{1}{\beta}}}{w_i^{\theta}}\right)\left(\frac{w_j^{\theta}}{T_j^{\frac{1}{\beta}}}\right) t_{ij}^{-\theta} \tag{6}$$

[6] Let $\pi_{ij} = \frac{X_{ij}}{X_j}$. Then, $\frac{\partial \pi_{ij}}{\partial T_j} < 0$, or there is an inverse relationship between the expenditure on goods from i and the direction of T_j. And, $\frac{\partial \pi_{ij}}{\partial T_i} > 0$, or there is an positive relationship between the expenditure on goods from i and the direction of T_i.

[7] Chen et al. (2020) study this substitution behavior and its implications for U.S. crop profits.

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 (6) is a gravity-like equation commonly found in the trade literature, where the expressions in parentheses are the size terms.[8] In contrast to gravity equations derived from the demand side, normalized trade depends on regional comparative advantage. For example, the size term associated with the exporter increases as she becomes more productive (i.e., T_i increases), but decreases as her production expenses rise (i.e., w_i increases). The technology-expense relationship is inverted for the importer. The more expensive it is for the importer to produce (i.e., w_j increases) in her region, the more she relies on exports. In contrast, the more productive she becomes (i.e., T_j increases), the more she consumes domestic production.

3 Empirical Strategy

The U.S. crop markets are formed by several producers with heterogeneous production technologies, but there are only three major consumers of U.S. crops: Food processors that process crops for human consumption, meat producers that buy cereals to feed their animals, and exporters that resell U.S. domestic production overseas. This distinction has empirical implications since substitution effects (i.e., σ in Equation (2)) are different depending on the consumer. For example, ranchers use specific types of grains to feed their animals, so their elasticity of substitution is low. On the other hand, exporters' demand for domestic crops is derived at the international level. Food processors' demand for domestic crops is derived by domestic consumers at groceries stores, restaurants, schools and other institutions.

To homogenize consumption and to account for the substitution effects between crops varying across different consumer groups, I drop foreign imports and exports and instead just focus on domestic trade flows, excluding animal feed grains. Figure 1 describes the consumption of the three crop categories considered here as classified by the Standard

[8] A further re-arrangement of parentheses allows me to define w_i^θ and $T_j^{\frac{1}{\beta}}$ as multilateral resistance terms that prevent trade between the two regions.

Classification of Transported Goods (SCTG). Crops for human consumption are SCTG 02 and SCTG 03 that encompass fruits, vegetables and some cereals. SCTG 04 refers to cereals used to feed animals. Most crops produced in the U.S. are consumed domestically (88%) and 86% of domestic consumption is processed for human consumption. Therefore, my analysis focuses on largest aggregation of crops: Farmers' crop production for human consumption.

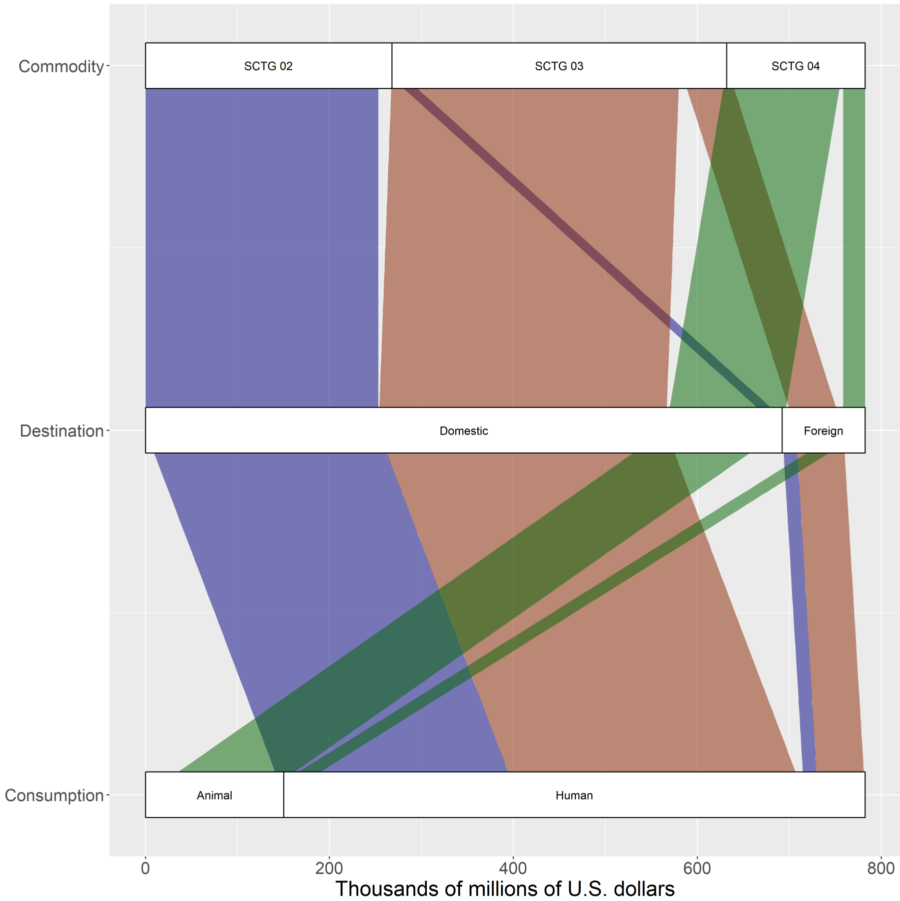


Figure 1: Consumption of U.S. crop production.
Note: SCTG 02 includes cereals such as wheat, corn and rye. SCTG 03 includes fruits and vegetables. SCTG 04 includes cereals for animal consumption. Only SCTG 02 and SCTG 03 are crops for human consumption. Analysis focuses on domestic consumption of crops processed for human consumption.

3.1 Data

My data come from the fourth version of the U.S. Freight Analysis Framework (FAF4) 2017 prepared for the Bureau of Transportation Statistics (BTS) and the Federal Highway Administration (FHA). FAF4 estimates domestic data flows between all U.S. states for several commodities and is disaggregated into several freight modes including water, air and ground. FAF4 is constructed using the Commodity Flow Survey (CFS) for most types of commodities; however, agricultural goods are based on its CFS out-of-scope shipments, which use the USDA Census of Agriculture. My measure of crop trade flows is constructed by aggregating SCTG 02 and SCTG 03, so it includes fruits, vegetables and some cereals processed for human consumption.[9]

Table 1 describes the data for each of the variables used in my analysis. The top part of the table describes dyadic variables that capture attributes about the relationship between two states. The bottom part of the table describes monadic variables that capture attributes about states. Imports and exports are created using FAF4 data. All measures are in millions of 2017 U.S. dollars. Population density data are collected from the 2010 U.S. Census Bureau of Statistics and is measured in population per square kilometer. Labor expenses per harvested acre comes from the 2017 U.S. Census of Agriculture and is measured in 2017 dollars. Climate variables that affect agricultural output during the growing season are precipitation and temperature during summer. Precipitation is measured in cubic centimeters, and temperature is measured in degrees Celsius. Climate data are collected from the Parameter-elevation Regression on Independent Slopes Model (PRISM) data base (PRISM, 2011). I calculate distance between polygons' centroids in a shapefile, using the Geoda software. My measure of distance is in kilometers.

Because virtually all agricultural activity occurs outside cities and many of the variables described earlier can be heavily influenced by urbanization, I follow a two-step aggregation of my data variables. First, all data is obtained at the county level for all counties in the contiguous U.S. Next, metropolitan and highly populated counties are dropped. Finally, I calculate state averages excluding metropolitan and high population counties. This aggregation allows me to reduce weight from highly populated states that are likely to have low agricultural production levels such as Rhode Island.

Using my trade data, I plot the structural relationships in Equation (6). In Figure 2,

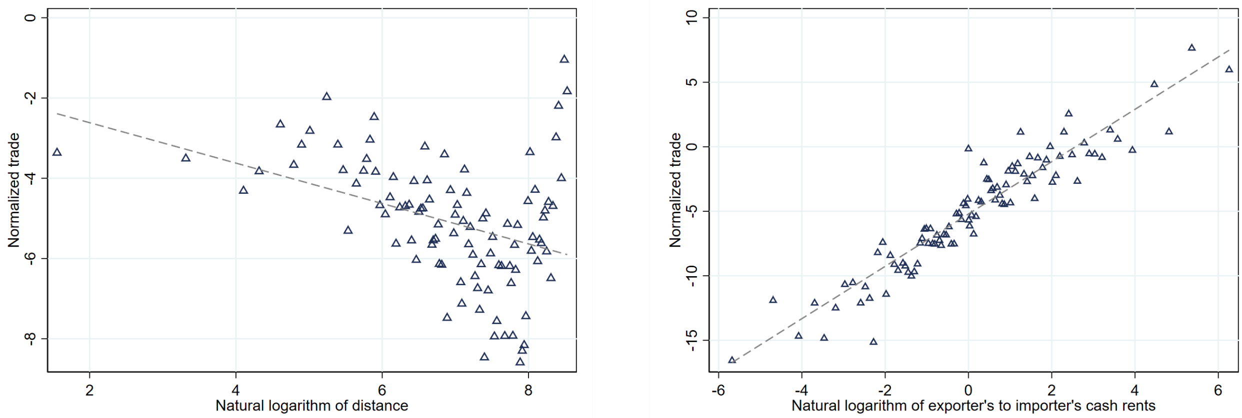
[9] Crop trade flows are shown in Figure A.1. Panel (a) shows trade dynamics between all U.S. climate regions. Panel (b) shows trade dynamics between all U.S. states. Most crop trade flows are within the state as shown in the diagonal of the heat maps, but there are larger trade dynamics among U.S. states.

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

Dyadic Variables	Mean	S.D.	Min	Max
Distance	1827.27	1295.40	0	5179.18
Contiguity	.10	.29	0	1
Observations				2,304
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
Labor expenses per harvested acre	124.18	160.48	104.50	710.45
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
Observations				48

Note: All monetary measures are in 2017 U.S. dollars. Imports and exports are created using FAF4. Population density is measured in population per square kilometers. Precipitation is measured in cubic centimeters, and temperature is measured in degrees Celsius.

I study the relationship between normalized trade and its determinants as illustrated in Equation (6). While bilateral trade costs are not observed, distance is a commonly accepted proxy. Panel (a) shows that trade decreases as the distance between regions increases. Equation (6) predicts a negative relationship between the size terms and normalized trade. While labor expenses per harvested acre is observed, agricultural capacity, T_k, is not directly observed. I approximate the size terms using cash rents since Ortiz-Bobea (2019) shows that crop cash rents reflect farmers' technology adjusted by their expenditure. Panel (b) shows the relationship predicted in Equation (6).



(a) Distance

(b) Cash rents

Figure 2: Relationship between gravity equation and crop data.
Note: Each point is an average of its closest observations. Equation (6) suggests an inverse relationship between normalized trade and distance. Panel (a) shows this relationship. Equation (6) suggests a positive relationship between the ratio of the size terms and normalized. Panel (b) shows this relationship.

In the next part, I recover the structural parameters in Equation (6), using the data discussed in this part.

3.2 Recovering structural parameters

Recovering the structural parameters θ, T_i and t_{ij} requires a two-step approach. First, Equation (6) is parameterized with the log-linearization of the expression. Equation (7) is the regression model, where the size terms are denoted by S_i for the exporter and S_j for the importer and are approximated by 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 (8), where the size terms come from Equation (6). Because θ in Equation (8) is associated with an observable variable, θ can be recovered. Here, τ_k is the error term. My measure of the share of labor expenses per harvested acre (i.e., β in Equation (6)) is 0.12 as reported by the USDA in its 2017 Census of Agriculture.[10]

$$\ln \frac{X'_{ij}}{X'_{jj}} = -\theta \ln t_{ij} + S_i - S_j + \epsilon_{ij} \tag{7}$$

$$\hat{S}_k = \alpha + \frac{1}{\beta} \ln T_k - \theta \ln w_k + \tau_k \tag{8}$$

The estimation of Equation (7) is carried out through the use of dummy variables. Since bilateral trade costs are not observed, I approximate them by a contiguity dummy that indicates whether two states share the same border and six dummies corresponding to distance bins (0,865], (865,1730], (1730,2595], (2595,3460], (3460,4325] and (4325, Max]. Since I 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. To ensure the comparability of my size term estimates, all fixed effects must be estimated in the same regression, so I

[10] I consider $\beta = 0.12$, the weighted average of my two crop aggregations, despite that SCTG 03 is more labor intensive than SCTG 02. For robustness, I test $\beta \epsilon [.08, .19]$ where 0.08 is the share of labor expenses for SCTG 02 and 0.19 is the share of labor expenses for SCTG 03. Results remain equivalent in significance and magnitude. The implications of the selection of intermediate inputs on the estimation of the comparative advantage parameter are studied in the appendix.

drop the constant term from the model. Notice that the estimation of Equation (7) will drop all zero-trade observations (i.e., $X_{ij} = 0$).

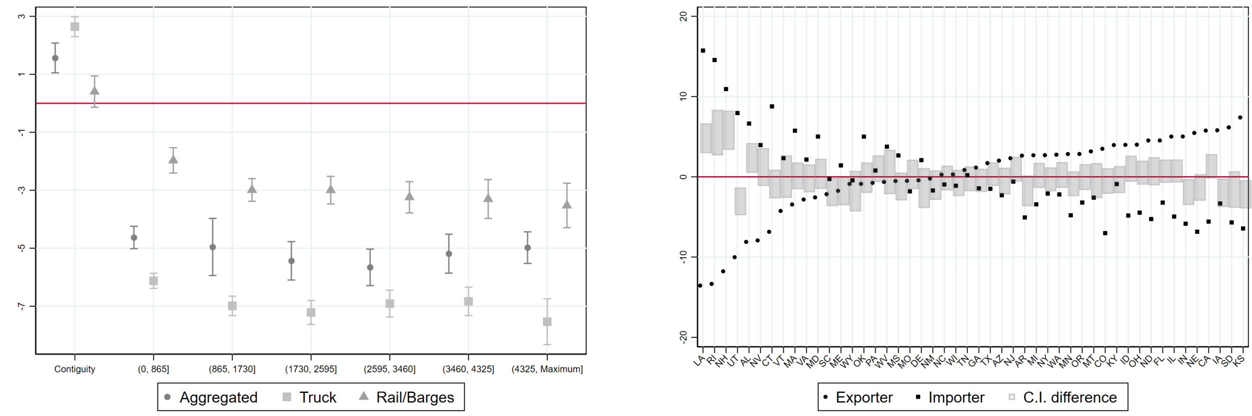
Because trade between regions is not symmetric as shown in Figure A.1, the variance-covariance matrix is assumed to have diagonal elements $\sigma_1^2 + \sigma_2^2$ that affect both two-way trade and one-way trade, and certain nonzero off-diagonal elements σ_2^2 that affect only two-way trade. For this reason, I employ the Feasible Generalized Least Squares (FGLS) estimator.

Figure 3 reports estimates from Equation (7). In panel (a), I report the proxy estimates for bilateral trade costs (Aggregated). As expected, whether two states share the same border predicts more trade between the states. The trade literature has long supported an inverse relationship between trade and distance. My results indicate that the cost of transporting crops increases with distance, but transportation costs flatten for the last two distance bins. I attribute this to freight mode decisions. While most crop production is shipped within short distances by truck, the volume shipped by truck decreases with distance but increases for rail and barges. To shed light on this hypothesis, I estimate Equation (7) by differentiating trade by freight mode. Not only the U-shape relationship disappears, but as expected, trade decreases with distance.[11]

In panel (b), fixed effect estimates are reported. The estimates associated with the size terms are structurally symmetric as shown in Equation (6). Deviations from symmetry represent non-market influences that affect either the imports or exports from a region. For instance, international trade applications of the gravity model interpret each set of fixed effects as competitiveness and openness for the exporter and importer side respectively. The distinction reflects institutional and policy differences that affect specific countries such as weak government institutions, affecting exports, and policies that encourage citizens to consume domestically sourced goods, affecting imports. I 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 me from testing whether point estimates are statistically different from zero since each set

[11] The distinction between freight mode also reflects the idea that different levels of infrastructure affect bilateral trade cost and not only trade barriers.

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 confidence interval for the whether each pair is equal to each other is represented in the gray bars. Deviations for symmetry are observed for Louisiana, Rhode Island, New Hampshire and Utah, but symmetry remains for all other states.



(a) Bilateral trade costs

(b) Size terms

Figure 3: Estimation results from gravity equation: Distance and importer- and exporter-size effects.

Note: R^2 is 0.97 with 1,334 observations. The imposed symmetry of our structural model prevents me 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 confidence interval for the whether each pair is equal to each other is represented in the gray bars.

Using estimates for the size terms, I estimate their reduced form, Equation (8), to recover θ. Since agricultural capacity is not observed, I proxy it using historical precipitation and temperature for each U.S. state, following a quadratic polynomial with an interaction term. Because I expect high labor expenses per acre to be associated with high levels of agricultural capacity, I employ the 2-Stage Least Squares (2SLS) estimator. My instrumental variable is average population density in rural counties within each U.S. state. My construction of population density variable ensures that my instrument affects labor expenses per acre, but not other determinants of agricultural capacity such as climate.[12]

[12]The threat to 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. My instrument is weakly and negatively correlated with temperature in the growing season. In fact, a large part of the

Table 2 reports results from the estimation of Equation (8). 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. Variance inflation factors of climate variables are above 100 in every regression, so climate estimates are highly uninformative.[13] My conceptual framework predicts θ to be positive and greater than 1, so the coefficient associated with labor expenses per harvested acre must be negative and less than 1. The results from OLS estimations show that θ is not statistically different from zero. As expected, correcting for endogeneity brings larger and statistically different from zero estimates of θ. The exporter size terms indicates that $\theta = 1.922$, but the importer size terms indicates that $\theta = 2.468$. Table 2 also reports the first stage and demonstrates that my instrument is not a weak one.[14]

The implication of the comparative advantage structural parameter carry to welfare analyses in next section since θ controls the variability in agricultural productivity (the larger θ, the less variability in productivity). Thus, a final consideration is the decision of using either $\theta = 1.922$ or $\theta = 2.468$. To my knowledge, no theoretical framework provides insights about the magnitude of θ in agricultural studies or a further calibration beyond the estimation in this section. Therefore, I rely on the work of Reimer and Li (2010) as guidance. Their point estimates for θ are no lower than 2.52 and no higher than 4.96, and employ several estimation techniques. Reimer and Li (2010) estimate $\theta = 2.83$ using a Generalized Method of Moments approach with crop data. The authors also report that their largest estimate of $\theta = 4.96$ is based on a proxy estimation using the relative prices of the commodities analyzed, but Simonovska and Waugh (2014) show the use of such proxies systematically overestimates θ. Finally, Reimer and Li (2010) report that their lowest $\theta = 2.52$ uses maximum likelihood and a parametrization of the Fréchet

variation in agricultural productivity is explained by climate and land characteristics, ensuring that population density only affects labor expenses per harvested acre (Liang et al., 2017).

[13] Because the coefficient I am interested in is θ, climate proxies are just used as control variables.

[14] A concern associated with the estimations in Table 2 is the finite sample properties of IV estimator. Andrews and Armstrong (2017) report that exactly identified models with low number of observations have undesired properties (i.e., IV estimator is consistent, not unbiased), but the authors propose an estimator that is unbiased. I 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	-1.053	-1.922***	-1.491*	-2.468***
	(0.791)	(0.769)	(0.803)	(0.769)
Temperature	1.75	1.005	2.219	1.386
	(2.915)	(2.798)	(2.960)	(2.708)
Precipitation	-0.14	-0.109	-.114	-0.084
	(0.316)	(0.287)	(0.320)	(0.281)
Temperature^2	-0.036	-0.019	-0.419	-0.023
	(0.058)	(0.052)	(0.059)	(0.051)
Precipitation^2	0.001	0.002	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Interaction	0.002	-0.002	-0.004	-0.009
	(0.015)	(0.016)	(0.016)	(0.015)
Constant	-14.708	-2.153	-18.272	-4.150
	(37.707)	(35.413)	(38.333)	(34.580)
	First Stage			
Population Density		1.093***		1.093***
		(0.101)		(0.101)
F-statistic		29.72		29.72
R^2	0.08	0.78	.13	0.78
Observations	48	48	48	48

Note: Labor expenses and population density are natural logarithm values.Coefficient associated with labor expenses is comparative advantage. Values in parentheses are robust standard errors. Coefficients for weather variables are recovered up the constant $\frac{1}{\beta}$; *p < 0.10; **p < 0.05, ***p < 0.01.

distribution. Because my estimate for θ using the importer size terms as dependent variable falls closer to the estimates found in Reimer and Li (2010), I choose $\theta = 2.486$ as my preferred value for comparative advantage. I explore the comparative advantage implications of my selection of θ in the following subsection.

3.3 Comparative advantage

To analyze the comparative advantage of each U.S. sate, Equation (8) is re-arranged into the following equality: $\hat{T}_i = (e^{\hat{S}_i} w_i^{\hat{\theta}})^{\beta}$. Using labor expenses per harvested acre, the estimates for the exporters' size term, my preferred value for $\theta = 2.468$, and $\beta = 0.12$, I estimate the value of agricultural capacity of each state. Thus, each state's exporter size terms can be decomposed into an agricultural capacity component and a labor expense component. This decomposition is shown in Figure 4.

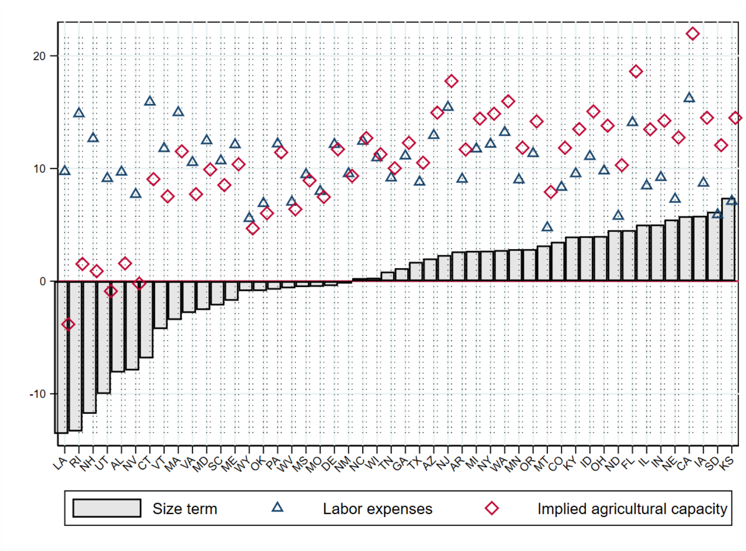


Figure 4: Comparative advantage (exporter size-term) decomposition.

Note: Figure reports size terms estimates obtained using Equation (8): natural log of the implied level of agricultural capacity and natural log of labor expenses per harvested acre in each U.S. state multiplied by $\theta = 2.468$. Implied level of agricultural capacity is $T_i = (e^{\hat{S}_i} w_i^{\theta})^{\beta}$.

All else constant, Equation (6) implies that net exporters have high levels of agricultural capacity relative to their labor expenses ($T_i^{\frac{1}{\beta}} > w_i^{\theta}$). This is because regions with relatively high levels of agricultural capacity can specialize in crop production. Similarly, net importers have low levels of agricultural capacity relative to their labor expenses ($T_i^{\frac{1}{\beta}} < w_i^{\theta}$). Therefore, the size term can be interpreted as a state's comparative advantage. Figure 4 shows that a state's comparative advantage largely depends on its agricultural capacity. While labor expenses per harvested acre remain close to the national average, agricultural capacity can take extreme values. When agricultural capacity surpasses the values of labor expenses, the state becomes a net exporter.

My results indicate that Kansas, South Dakota, Iowa, California, Nebraska, Indiana, Illinois and Florida have the largest specialized crop production in the U.S. Not surprisingly, only these nine states account for over half of all domestic crop exports. 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 labor expenses within the state. This emphasizes the importance of reducing labor expenses or mechanize production to compete. On the other hand, Louisiana, Rhode Island, New Hampshire, Utah, Alabama and Nevada have the lowest levels of agricultural capacity and high labor expenses. These six states export less than 2% of domestic crop production and import up to four times what they export.

In the next section, I employ the structural parameter for competitive advantage and my trade data to run three simulations. First, I study improvements of using U.S. domestic trade data over the international crop trade data employed by Reimer and Li (2010) through an autarky simulation. Then, I simulate welfare gains caused by two opposing policy recommendations: Improvements of local agricultural capacity and reductions in the cost of trade. The former simulation reflects welfare improvements from policies that promote local agriculture. The latter simulation reflects welfare improvements from policies that facilitates or promote trade between states such as improving the infrastructure to transport goods across state boundaries. Finally, I use welfare simulations along with a resilience measure to study states' resilience to local and foreign weather shocks.

4 Welfare and Resilience Simulations

My welfare measure is given by changes in real expenditure on crops. My comparative advantage parameter (i.e., $\theta = 2.468$) and my trade data (i.e., Figure A.1) are employed in my welfare analyses[15] (Arkolakis et al., 2012; Baier et al., 2019). First, I denote a region's income from crop production 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 into Equation (9).

$$c_i L_i = \sum_J \frac{T_i (c_i t_{ij})^{-\theta}}{\sum_K T_k (c_k t_{kj})^{-\theta}} X_j \tag{9}$$

Using hat-algebra, I define an equilibrium measure in changes in the structural parameters: Equation (10). Here, $\hat{c}_i = \frac{c_i'}{c_i}$ is the change in expenses per harvested acre, $\hat{T} = \frac{T_i'}{T_i}$ 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 share that indicates how much of $j's$ expenditure comes from i before the

[15]The Stata command is ge_gravity, which solves a general equilibrium with most of the characteristics described in this manuscript by employing a fixed-point algorithm: One sector and constant returns to scale technologies. I thank Dr. Zylkin for modifying the .ado file to include equilibrium disturbances by technology changes (i.e., T_k).

weather event. $\hat{t}_{ij}^{-\theta} = e^{\tau}$, where $\tau = 0$ if no change in bilateral trade costs is analyzed.

$$Y_i \hat{c}_i = \hat{T}_i \hat{c}_i^{-\theta} \sum_J \frac{\hat{t}_{ij}^{-\theta} \pi_{ij}}{\sum_K \pi_{kj} \hat{T}_k \hat{c}_k^{-\theta}} \hat{X}_j \tag{10}$$

Finally, I define a state's change in nominal expenditure as $\hat{X}_i = \frac{Y_i \hat{c}_i + D_i}{X_i}$, where D_i is an additive component to treat trade imbalances. Then, nominal expenditure change is normalized by change in prices: $\hat{p}_i = [\sum_k \pi_{ki} \hat{T}_k \hat{c}_k^{-\theta}]^{\frac{-1}{\theta}}$. To account for input intermediates as previously defined by $c_i = w_i^{\beta} p_i^{1-\beta}$, Equation (10) is reduced into my final expression of welfare given by Equation (11), where $\hat{W}_i$ is the change of welfare in i. [16] Contrary to the Ricardian trade application on agriculture of Reimer and Li (2010), I consider intermediate input consumption. As my expression of welfare suggests, the larger the share of intermediate inputs $(1-\beta)$, the higher the welfare effect. This is because extreme weather events not only hinder production in the region, but will cause disruptions in the production of other regions further magnifying the welfare effect.

$$\hat{W}_i = \left(\frac{\hat{X}_i}{\hat{P}_i}\right)^{\frac{1}{\beta}} \tag{11}$$

Equilibrium deviations caused by weather events and food policy implementations can be analyzed using Equation (10) and Equation (11). I simulate the impact of extreme weather events in a state by a reduction of the T_i associated with the affected state. A policy that promotes local agriculture by improving local agricultural productivity has the opposite effect: Increases of T_i. Finally, enhancements of food supply chains between U.S. states are simulated by reductions in t_{kj} for all k states.

I use Equation (11) to construct a state's resilience to an extreme weather event after the implementation of a specific food policy. Equation (12) is my resilience measure. Here, $\hat{W}_i^{shock}$ is the state's welfare reduced by the weather event, and $\hat{W}_i^{policy}$ is the bounce back after the implementation of the food policy.

[16] While the goal of my analysis is to inform regulators about the best policy each U.S. state should purse to mitigate welfare declines caused by weather shocks, welfare measures can be comparable across U.S. states. The theoretical model of Eaton and Kortum (2002) 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, and a 10% welfare decline in both states can be thought as both consumers reducing their food expenditure by the same level.

$$R_i^{policy} = \hat{W}_i^{policy} - \hat{W}_i^{shock} \tag{12}$$

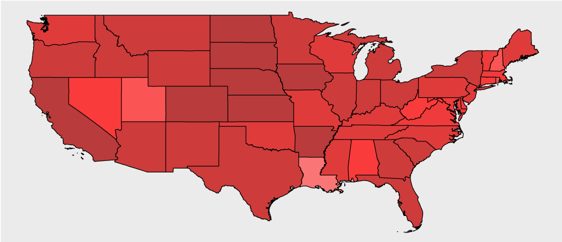
4.1 Autarky

A simple way to assess the advantages of using the U.S. domestic setting over the international setting is to analyze welfare losses associated with a movement to autarky. Arkolakis et al. (2012) demonstrate that welfare losses caused by moving to autarky can be expressed in terms of the fraction of a state's expenditure on domestic production. Thus, Equation (11) is reduced into Equation (13). This intuitive result illustrates that the higher the reliance on imports is, the higher the loss when the level of imports is reduced. Figure A.1 shows most domestic production is consumed locally by most states. Nevertheless, the results of my counterfactual simulations show large losses associated with a movement to autarky. Figure 5 illustrates the spatial distribution of my results.

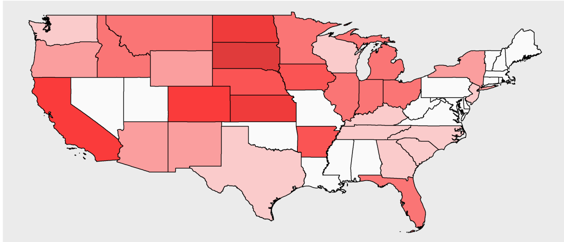
$$\hat{W}_i^A = \pi_{jj}^{\frac{1}{\theta\beta}} \tag{13}$$

In order to compare my results to those reported by Reimer and Li (2010), I ran a simulation without considering intermediate inputs (Panel (a)) and considering intermediate inputs (Panel (b)) separately. Reimer and Li (2010) report welfare losses ranging from 0% to 5.5%. In contrast to their findings, my counterfactual scenario shows losses ranging from 4% for South Dakota to 64% for Louisiana. The national welfare loss is 24%. Accounting for intermediate inputs, autarky in the U.S. produces a 79% average welfare loss. The results of my autarky counterfactual provide evidence that the U.S. domestic market of crops is farther away from autarky than the international market of crops analyzed in Reimer and Li (2010). My results imply that fewer frictions, perhaps only limited to geography, exist in the U.S when compared to international trade.

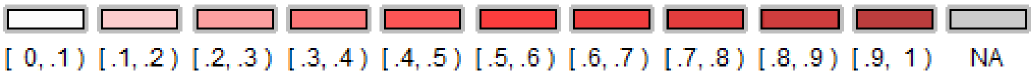
For some states, losses are significant, implying a reduction of their expenditure to a third of its baseline value. Louisiana, Rhode Island, New Hampshire, Utah, Alabama and Connecticut have the lowest agricultural capacity in the U.S. and spend less than 25% of their crop expenditure domestically. On the other hand, Kansas, South Dakota, Iowa,



(a) Autarky: No intermediates



(b) Autarky: Intermediates



	No intermediates				Intermediates			
	Mean	(S.D.)	Minimum	Maximum	Mean	(S.D.)	Minimum	Maximum
$\hat{W}_i^A$	0.76	(0.154)	0.36	0.96	0.21	(0.199)	0.00	0.71

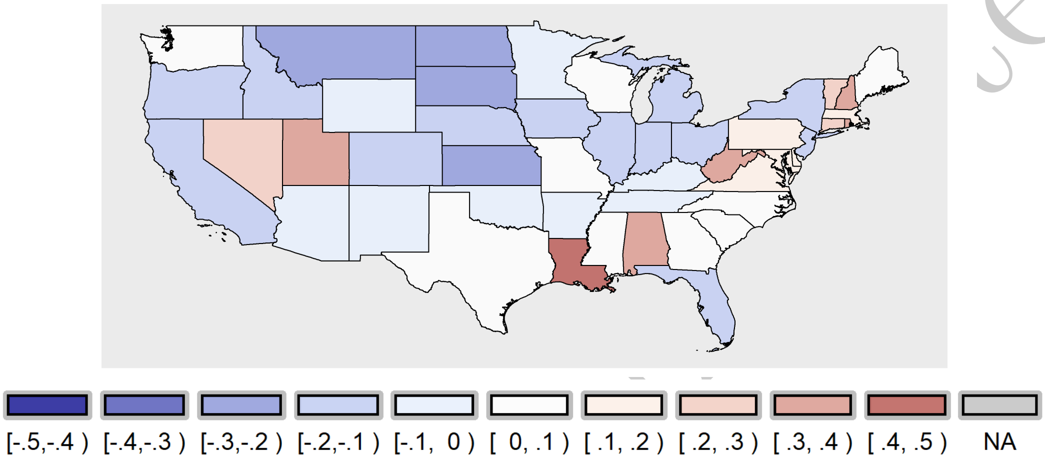
Figure 5: Autarky simulation results.

California, Nebraska, Indiana, Illinois and Florida have the highest agricultural capacity and spend about 75% of their crop expenditure domestically, so their welfare is reduced by no more than half after accounting for intermediate inputs.

Because agricultural production requires intermediate inputs such as seeds from other farms, all states' welfare is reduced drastically after accounting for intermediate inputs. For example, Maryland spends 30% of their crop expenditure domestically. Under autarky, Maryland's welfare is reduced 70%, but after accounting for intermediate inputs, its welfare is reduced to up 98%. Similarly, Illinois consumes 75% of its crop expenditure domestically, but its welfare is reduced from a 11% loss to a 63% loss after accounting for intermediate inputs.

4.2 Local agriculture and reduction of the cost of trade

Both improvements in local agricultural productivity and enhancements in food supply chains have welfare gains for consumers. By themselves, welfare results for each policy counterfactual serves as an analysis of the potential welfare gains from a policy that aims to promote local agricultural productivity and a policy that aims to improve the state of U.S. infrastructure. Equation (11) suggests that increases in expenditure and a decline of prices have a positive effect on consumers' welfare. Local agricultural productivity increases the supply of food and in turn reduces food prices, so this food policy has a negative effect on prices. Nevertheless, each food policy is costly both politically and economically. Thus, comparing both opposing policy recommendations provides insights of what policy achieves the highest benefits for consumers and why. I increase each state's agricultural capacity by 5% to simulate improvements in local agriculture, and then compare it with 5% reductions in each state's bilateral trade costs that simulate enhancements in food supply chains. I run each state's simulation separately to control for spillovers from other states. Figure 6 illustrates my results.



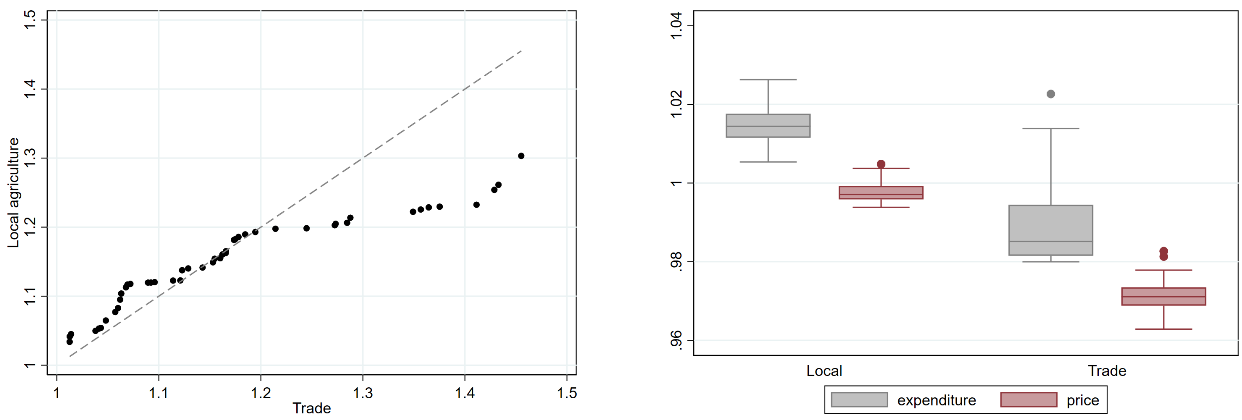
	Local				Trade			
	Mean	(S.D.)	Minimum	Maximum	Mean	(S.D.)	Minimum	Maximum
$\hat{W}_i$	1.15	(0.065)	1.03	1.30	1.17	(0.125)	1.01	1.46
$\hat{X}_i$	1.01	(0.005)	1.01	1.03	0.99	(0.010)	0.98	1.02
$\hat{P}_i$	0.99	(0.003)	0.99	1.00	0.97	(0.004)	0.96	0.98

Figure 6: Welfare gains from each opposing policy recommendation.

Note: Difference is measured by $\hat{W}_i^T - \hat{W}_i^L$, so the darker the state the higher the relative gain from a food policy that reduces trade costs (T) compared to a food policy that improves local agricultural (L) productivity.

On average, U.S. consumers' welfare is 13% higher under reductions of trade costs than under improvements of local agricultural productivity. As expected, the average expenditure increases and the level of prices reduces under a policy that promotes local agriculture. Both policy's effects on expenditure and prices improve consumers' welfare. On the other hand, a food policy that promotes trade has the opposite effect on food expenditure: It reduces food expenditure by 2%. This food policy, however, is welfare improving, since the reductions in expenditures in this scenario are mostly attributed to reductions in food prices. Furthermore, welfare heterogeneity indicates that states differ in the efficiency of each policy. The map in Figure 6 compares welfare gains from a trade policy relative to a local agricultural policy (i.e., $\hat{W}_i^T - \hat{W}_i^L$). States like Louisiana, Nevada and Rhode Island that have low levels of agricultural productivity benefit the most from a trade policy and the least from a local agricultural policy. In contrast, large agricultural hubs such as California, Florida and some Midwestern states benefit the most from a policy that improves their local agricultural productivity and the least from a trade policy.

To further explore the mechanisms and welfare distributions caused by the two food policies, Figure 7 presents a quantile analysis (Panel (a)) for each policy's welfare distribution and a boxplot analysis (Panel (b)) for each policy's impact on expenditure and prices respectively. The quantile analysis ranks the beneficiaries from each food policy and compares them by percentiles. This analysis indicates that the large welfare divergence between each food policy comes from the top 25% beneficiaries of the trade policy: Louisiana, Rhode Island, New Hampshire, Connecticut, Utah, Alabama, Massachusetts, Maryland, Oklahoma, Nevada, West Virginia and Mississippi. Figure 4 indicates that most of these states have low agricultural capacity and low comparative advantage. Thus, this food policy is highly progressive. For the bottom three quantiles, there is a consistent symmetry except for some states in the second quantile.



(a) Quantile analysis

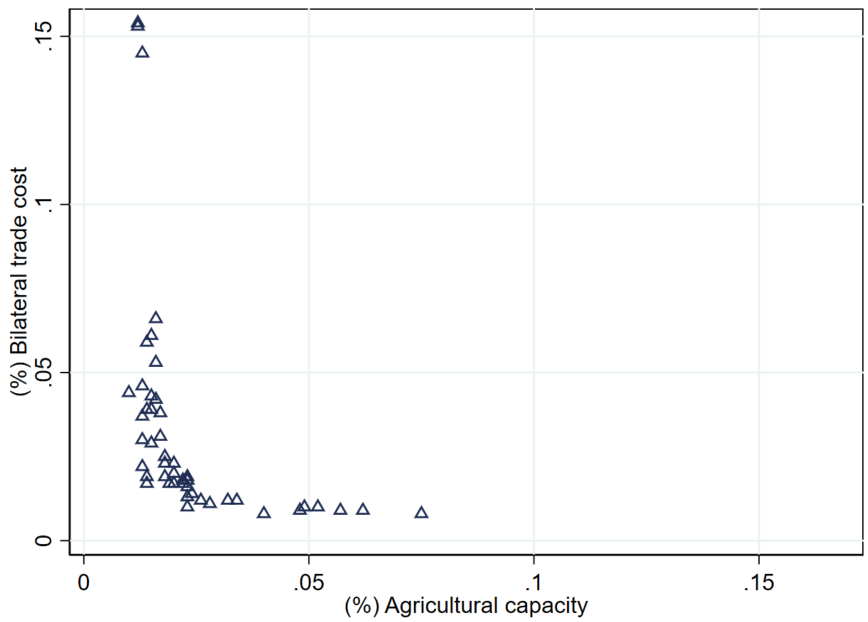
(b) Boxplot analysis

Figure 7: Welfare distribution analysis.

The impact on expenditure by a food policy that promotes local agriculture is positive for all states; but the impact on prices is negative or close to zero for some net importing states such as New Hampshire, Nevada and Louisiana. This indicates that the mechanism through which local agricultural productivity improves consumers' welfare is through domestic consumption, so states with low agricultural productivity have little to gain from improvements in local agricultural productivity. A food trade policy's impact on expenditure is mostly negative for the large majority of states, but they are accompanied by large reductions in the level of prices. This indicates trade improves consumers' welfare through prices.

The extent to which changes in the state's T_i (agricultural capacity) are comparable to changes in all k state's t_{ki} (bilateral trade costs), and in turn the opportunity cost of each food policy, is a caveat of my analysis. The Ricardian trade framework of Eaton and Kortum (2002) indicates that both structural parameters are general terms encompassing the determinants of the state's agricultural productivity (for T_i) including technology, labor productivity and climate, and the cost of shipping production (for t_{ki}) such as the current state of transportation infrastructure and the distance between the two states. Eaton and Kortum (2002) compare the role that bilateral trade costs and technology plays in determining a country's comparative advantage, but these comparison are purely theoretical since they analyze the autarky and zero-gravity scenarios (i.e., all $t_{ij} = 1$). To my knowledge, no one has reported comparing welfare results from counterfactual scenarios that exploit different structural parameters.

To study the extent to which my simulation results can be compared, I calculate the necessary change in each set of structural parameters to achieve a 5% welfare improvement for each U.S. state. Figure 8 describes the results from this exercise. Consistent with the results in Figure 4, the larger the state's initial level of agricultural capacity, the lower the necessary increase of agricultural capacity to achieve the 5% welfare improvement. In other words, in states with low agricultural capacity such as Louisiana, New Hampshire and Alabama, large agricultural productivity investments are required to have significant welfare improvements. Large differences are found for some states reflecting the initial level of agricultural comparative advantage, but the difference between national averages is small. In fact, excluding states that fall above 5%, results suggest that the large majority of states benefit from improvement in agricultural capacity, but as results in the next section suggest, this is not the case in the face of extreme weather events.



	Mean	(S.D.)	Minimum	Maximum
Agricultural capacity	.024	(0.014)	0.010	.075
Bilateral trade costs	.033	(0.034)	0.009	.154

Figure 8: Levels of agricultural capacity and bilateral trade costs required to improve each state's welfare by 5%.
Note: (%) Bilateral trade costs reflects negative values. (%) Agricultural productivity reflects positive values.

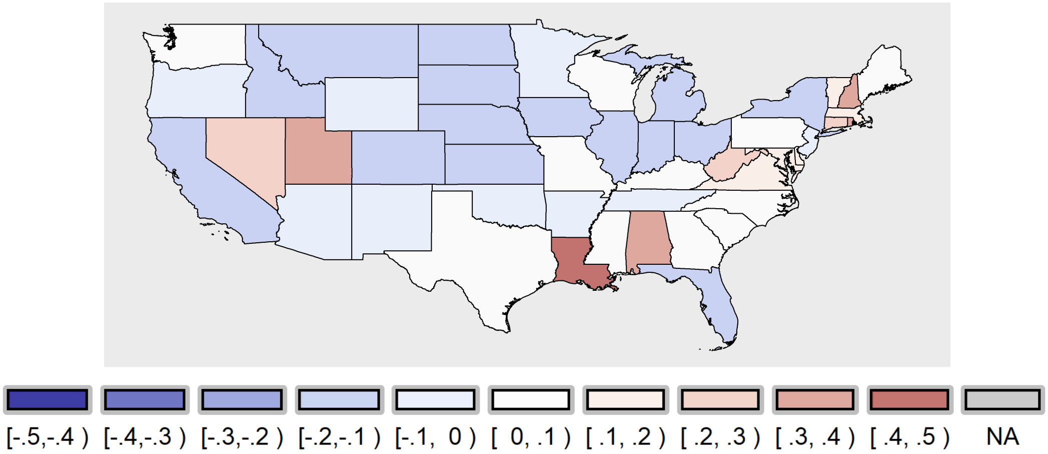
The analysis presented in this section serves three purposes. First, it provides evidence that trade and comparative advantage (i.e., specialization) benefits consumers' welfare more than local agriculture. The relative gains illustrated in Figure 6 and Figure 7 are driven by states with low comparative advantage that benefit little from improvements in local agricultural productivity. Secondly, solving Equation (11) for prices and expenditures is feasible, because there are as many equalities as unknown variables, but this is unfeasible with Equation (12) since there are twice as many unknown variables as there are equalities. Therefore, this section provides insights of how each policy creates resilience against weather shocks. On the one hand, a policy that promotes local agriculture creates resilience by increasing the food supply available to local consumers, but consumers in states with low agricultural capacity would not replace consumption losses by more local production. On the other hand, a policy that reduces the costs of trade creates resilience by increasing the availability of options that in turn reduce prices regardless of local production circumstances. Finally, I assess the extent to which food policies can be compared by analyzing what is required to achieve a fixed welfare level. While this comparison is a caveat of my analysis, the latter exercise provides some evidence the the resilience results in the next section are not invalid. Despite this, an ideal comparison should reflect the actual cost of the policies.

4.3 Resilience against weather shocks

A major concern of having regions relying on local agricultural production raised in this paper is food vulnerability caused by extreme weather events. Regardless of whether the state is a large agricultural hub or a net food importer, weather shocks can raise food prices, affecting disproportionately the poorest households. For states that consume most of its domestic food production, local weather shocks can have severe repercussions if states cannot import easily from other states. Similarly, foreign weather shocks ripple through food prices into states that are net importers. In this section, I evaluate both opposing food policies as a response to each type of weather event. First, I focus on local weather shocks. That is, how states respond to extreme weather events within their region. Then, I focus on two foreign weather shocks relevant for the U.S. during the last decade. One simulates the impact of the California drought (2012-2017) on its trading partners, and the other one simulates the impact of the Midwestern drought (2012) on its trading partners.[17] Figure 9 illustrates the results for local weather shocks.

On average, the U.S. is 14% more resilient to local weather shocks by reducing the cost of trade than by improving local agricultural capacity. Even for large agricultural hubs that benefit the most from local agricultural improvements, the difference between the two policy impacts is small: California (.08), Colorado (.06), South Dakota (.06), Nebraska (.06), Arkansas (.05), Iowa (.04), North Dakota (.04), Kansas (.03), Illinois (.03), Florida (.02), Indiana (.02) and Minnesota (.01). On the other hand, net food importers that

[17] Midwestern states: Illinois, Indiana, Iowa, Kansas, Missouri, Nebraska, North Dakota, Ohio, South Dakota.



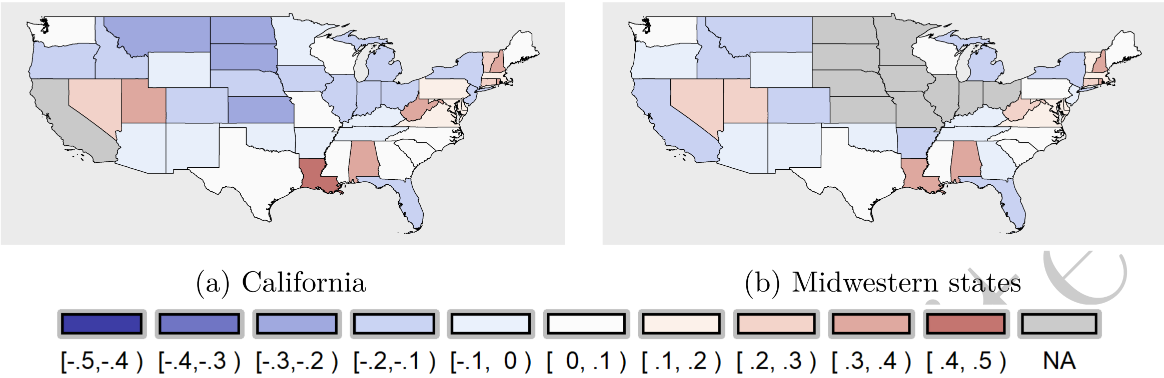
	Local				Trade			
	Mean	(S.D.)	Minimum	Maximum	Mean	(S.D.)	Minimum	Maximum
$\hat{R}_i$	0.12	(0.049)	0.03	0.23	0.16	(0.121)	0.01	0.44

Figure 9: Difference in resilience to local weather shocks from each opposing policy recommendation.

Note: Difference is measured by $\hat{R}_i^T - \hat{R}_i^L$, so the darker the state the higher the relative gain from a food policy that reduces trade costs (T) compared to a food policy that improves local agricultural (L) productivity.

benefit the most from reductions in trade costs have the largest differences such as Rhode Island (six times more), Louisiana (thirteen times more), Connecticut (three times more) and New Hampshire (ten times more). The results from Figure 6 and Figure 7 suggest that the large difference is driven by these states that benefit little from a local agriculture policy but largely from a trade policy.

Figure 10 illustrates the results for foreign weather shocks, except that the region impacted is excluded from the analysis. The spatial welfare distribution is similar to that caused by local weather shocks and implies that states with large agricultural productions are slightly better off with a policy that improves their local agriculture, while states that are net importers benefit largely with a policy that reduces their costs of trade. In both foreign weather events, the largest differences are driven by net food importers such as Alabama, Connecticut, Louisiana, New Hampshire, Utah and West Virginia. Some of the spatial differences between each foreign weather event are due to reliance on imports from the region affected. Although small, the distinction illustrates a mechanism not described in the previous section. For local weather shocks, states substitute domestic consumption for imports. In contrast, foreign weather events affect all importers, so all consumers compete for imports from other sources. In this context, it may be intuitive to opt for a local agriculture food policy, but results in Figure 10 indicate this is not the case.



(a) California

(b) Midwestern states

Figure 10: Difference in resilience to local weather shocks from each opposing policy recommendation.

	Local				Trade			
	Mean	(S.D.)	Minimum	Maximum	Mean	(S.D.)	Minimum	Maximum
$\hat{R}_i^{CA}$	0.15	(0.066)	0.03	0.31	0.17	(0.123)	0.01	0.45
$\hat{R}_i^{MW}$	0.15	(0.038)	0.04	0.23	0.19	(0.114)	0.04	0.42

Note: Differences are measured by $\hat{R}_i^T - \hat{R}_i^L$, so the darker the state the higher the relative gain from a food policy that reduces trade costs (T) compared to a food policy that improves local agricultural (L) productivity.

5 Conclusions

I study the effects of two opposing policy recommendations on consumers' welfare and their resilience to weather shocks in the U.S. One policy promotes local agriculture by improving local agricultural productivity, and another one enhances food supply chains between U.S. states. I find that welfare gains are 13% higher under reduced costs of trade than under improved local agricultural productivity. My results also indicate that U.S. resilience against weather shocks is higher under the enhanced efficiency of food supply chains than under improved agricultural productivity. The heterogeneity of my results suggests that each opposing policy recommendation's effectiveness depends on the states's relative comparative advantage.

The Ricardian trade model of Eaton and Kortum (2002) incorporates producers and consumers through prices and intermediate inputs and permits producers to have a level of relative comparative advantage. Failure to account for consumers' and producers' behavioral responses to weather shocks can distort welfare calculations. For instance, econometric models that do not allow for consumers' substitution can overstate welfare effects. I also employ a U.S. domestic trade data set to rule out non-market influences such as trade barriers and cultural proximity between regions. I present an autarky simulation to analyze the gains from trade in the U.S. market of crops and compare my results to those of Reimer and Li (2010).

My commodity aggregation and model specification allow for realistic substitution effects. In the U.S., farmers' production is bought by food processors that ship and sell to grocery stores. Food processors are likely to substitute consumption from one source to another rather than from one commodity to another. This producer-consumer relationship is captured by my model and data aggregation; however, my results aim to provide insights about final consumers. While this distinction has qualitative implications, it does not invalidate my conclusions because food processors' demand is derived demand: Policymakers should take into account that promoting local agricultural, rather than reducing the costs of trade, may not be as effective to protect food consumers' welfare when farmers face extreme whether events.

References

Anderson, J. E. (1979). A theoretical foundation for the gravity equation. *The American economic review*, 69(1):106–116.

Anderson, J. E. and Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American economic review*, 93(1):170–192.

Andrews, I. and Armstrong, T. B. (2017). Unbiased instrumental variables estimation under known first-stage sign. *Quantitative Economics*, 8(2):479–503.

Arkolakis, C., Costinot, A., and Rodríguez-Clare, A. (2012). New trade models, same old gains? *American Economic Review*, 102(1):94–130.

Baier, S. L., Yotov, Y. V., and Zylkin, T. (2019). On the widely differing effects of free trade agreements: Lessons from twenty years of trade integration. *Journal of International Economics*, 116:206–226.

Balogh, J. (2015). What role geographical distances and cultural proximity play in bilateral wine trade of Hungary? *New Ideas in a Changing World of Business Managament and Marketing*, page 35.

Biedny, C., Malone, T., and Lusk, J. L. (2020). Exploring polarization in U.S. food policy opinions. *Applied Economic Perspectives and Policy*, 00(00):1–21.

Burgess, R. and Donaldson, D. (2010). Can openness mitigate the effects of weather shocks? evidence from India's famine era. *American Economic Review*, 100(2):449–53.

Carrère, C. and Masood, M. (2018). Cultural proximity: A source of trade flow resilience? *The World Economy*, 41(7):1812–1832.

Chen, Z., Dall'Erba, S., and Nava, N. J. (2020). The U.S. interstate trade will overcome the negative impact of climate change on agricultural profit. *Submitted to American Journal of Agricultural Economics.*

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Fang, C. and Beghin, J. C. (2000). Food self-sufficiency, comparative advantage, and agricultural trade: a policy analysis matrix for chinese agriculture.

Felbermayr, G. J. and Toubal, F. (2010). Cultural proximity and trade. *European Economic Review*, 54(2):279–293.

Gephart, J. A., Rovenskaya, E., Dieckmann, U., Pace, M. L., and Brännström, Å. (2016). Vulnerability to shocks in the global seafood trade network. *Environmental Research Letters*, 11(3):035008.

Greene, C. (2018). Broadening understandings of drought–the climate vulnerability of farmworkers and rural communities in California (U.S.A.). *Environmental Science & Policy*, 89:283–291.

Liang, X.-Z., Wu, Y., Chambers, R. G., Schmoldt, D. L., Gao, W., Liu, C., Liu, Y.-A., Sun, C., and Kennedy, J. A. (2017). Determining climate effects on U.S. total agricultural productivity. *Proceedings of the National Academy of Sciences*, 114(12):E2285–E2292.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review*, pages 753–771.

Ortiz-Bobea, A. (2019). The role of nonfarm influences in Ricardian estimates of climate change impacts on U.S. agriculture. *American Journal of Agricultural Economics*.

PRISM (2011). Prism climate data. *Oregon State University*.

Puma, M. J., Bose, S., Chon, S. Y., and Cook, B. I. (2015). Assessing the evolving fragility of the global food system. *Environmental Research Letters*, 10(2):024007.

Reimer, J. J. and Li, M. (2010). Trade costs and the gains from trade in crop agriculture. *American Journal of Agricultural Economics*, 92(4):1024–1039.

Rodriguez, L., Horowitz, M., Espinoza, D., Aguilera, A., de la Torre, A., and Kaiser, L. L. (2015). The impact of the California drought on food security among rural families of Mexican origin. *Journal of Applied Research on Children: Informing Policy for Children at Risk*, 6(2):11.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2005). Will U.S. agriculture really benefit from global warming? accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1):395–406.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2006). The impact of global warming on U.S. agriculture: an econometric analysis of optimal growing conditions. *Review of Economics and statistics*, 88(1):113–125.

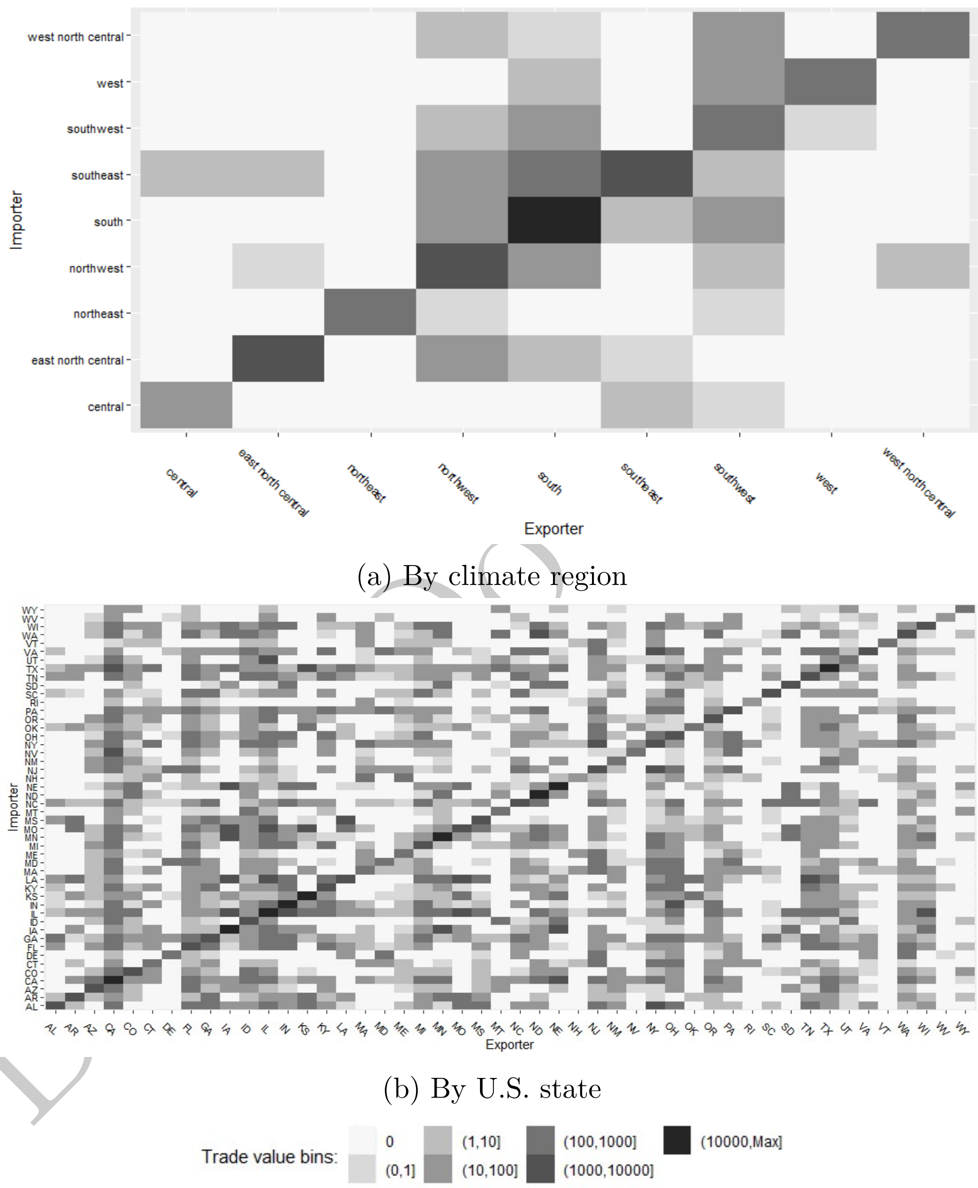
Simonovska, I. and Waugh, M. E. (2014). The elasticity of trade: Estimates and evidence. *Journal of international Economics*, 92(1):34–50.

Tortajada, C., Kastner, M. J., Buurman, J., and Biswas, A. K. (2017). The California drought: Coping responses and resilience building. *Environmental Science & Policy*, 78:97–113.

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 Geneva.

Appendices

A Origin and destination of U.S. domestic crop consumption



(a) By climate region

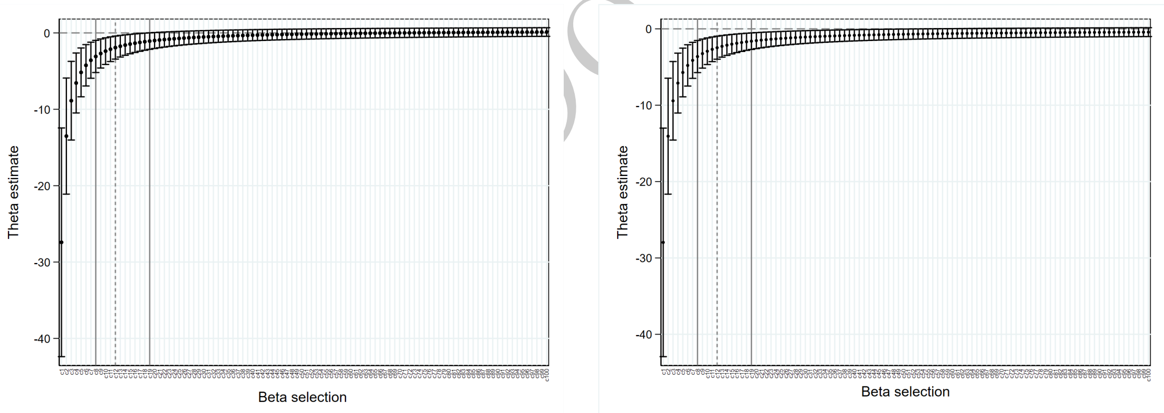
(b) By U.S. state

Figure A.1: Origin and destination of U.S. domestic crop consumption.

Note: Panel (a) is a heat map of crop trade between all U.S. climate regions. Panel (b) is a heat map of crop trade between all U.S. states. Most crop production is consumed within the state. All measure are in millions of 2017 U.S. dollars.

B Implications of intermediate inputs on the estimation of the comparative advantage parameter

The implications of my selection of the level intermediate inputs is studied in Figure B.1. Panel (a) focuses on the exporter size-term, while Panel (b) focuses on importer size-term. I consider $\beta = 0.12$, the weighted average of my two crop aggregations, despite that SCTG 03 (0.19) is more labor intensive than SCTG 02 (0.08). Results remain equivalent across $\beta \epsilon [.08, .19]$. However, as the selection of intermediate inputs increases, the estimated comparative advantage advantage attenuates. This is likely an artifact of measurement error. On the other hand, the assumption of no intermediate inputs such as in the case of Reimer and Li (2010) causes severe biases when using the two-step estimation employed by Eaton and Kortum (2002) and in this manuscript. This result should alert future researchers about appropriate selection of intermediate inputs both in welfare estimations and in the estimation of the parameter of comparative advantage.



(a) Exporter size-term

(b) Importer size-term

Figure B.1: Implications of intermediate inputs on the estimation of the comparative advantage parameter.