Who benefits from local agriculture?

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Abstract

Specialization in agriculture requires using farming practices that the general public perceive as unhealthy and detrimental to the environment. As a consequence, consumers' advocacy to shift food production back to local markets is gaining momentum. Based on a general equilibrium model of interstate crop trade, we conduct simulations to assess the impacts of different policies on the domestic food system. We analyze the welfare implications under a policy that improves local agricultural productivity. Then, we compare our results to those from an opposing policy recommendation that enhances food supply chains between U.S. states. The divergence between welfare impacts is driven by the benefits to net exporters of food with high levels of agricultural production. Our results suggest that policies that aim to improve local agricultural productivity may be regressive since they unambiguously benefit large agricultural producers.

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

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1 Introduction

Biedny et al. (2020) find that despite the sharp political polarization between the two main U.S. parties, both sides agree on a specific food policy issue: Shifting food production back to local markets. Proponents of policies that promote local agriculture generally raised environment and health concerns[1] (DuPuis and Goodman, 2005; Levkoe, 2011; Marsden, 2013). Their claim is that as distance between food sources and consumers increases, a disconnection between the adverse consequences of food production widens, hindering regulators' efforts to internalize negative externalities (Clapp, 2015). Even recently in the face of COVID-19, reliance on distant food sources caused misallocation of resources that increased food prices and food waste (Hobbs, 2020; Thilmany et al., 2020). Long before these most recent debates on inward- versus outward-looking approaches to production, however, economists have emphasized the gains to be had from trade and specialization (Krugman, 1981; Eaton and Kortum, 2002; Arkolakis et al., 2012). Trade advocates defend the position that specialized production reduces prices and expands access to efficiently produced products. While both sides are interested in addressing different pressing concerns, a re-assessment of the benefits of food trade should inform policy makers interested in promoting local agriculture.

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. More recent work (Rodriguez et al., 2015; Tortajada et al., 2017; Greene, 2018) considers the impact of severe agricultural productivity shocks; namely, farmworkers impacted by the California drought of 2012-2017. While previously cited works provide with convincing evidence about trade-induced resilience, the flip side of relying on trade is import dependency. 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

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

reliance can lessen food vulnerability to production shocks. Despite their internal validity and sophistication, most studies of food security are limited for being partial equilibrium analyses.

The latter two analyses of food vulnerability and trade, for instance, focus on consumer behavior and food production separately. Gephart et al. (2016) account for consumers' import substitution between goods, allowing the consumer to adjust her expenditure according to her tastes, but fail 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, causing welfare losses to likely be overstated. Therefore, a study of food security must account for general equilibrium effects.

Simultaneous modeling of consumers' utility and producers' profit optimization problems connects trade between regions with supply and demand determinants through a gravity-like equation (Anderson, 1979). Approaches based on gravity models are ideal for assessing the normative implications of various policy counterfactuals. 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' income. On the other hand, Eaton and Kortum (2002) propose a Ricardian analysis that emphasizes producers' relative comparative advantage through output prices and input costs.[2] A fundamental difference between the Armington-CES model and the Ricardian formulation of Eaton and Kortum (2002) is that the latter structurally captures the basis of comparative advantage. The approach starts by purging the model from dyadic variation that embodies bilateral determinants of trade such as how far apart two trade partners are from each other. Then, monadic variation can be further split into a productivity term and a production costs term.

[2]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).

Despite its strength and that innumerable gravity applications exist in the literature, empirical studies of agriculture base their analyses on a Ricardian notion of comparative advantage. Closer to our work, Reimer and Li (2009, 2010) exploit this formulation to study how yield variability will affect households for a selected group of countries, finding that openness to trade is positively related to countries' welfare impacts. In a similar manner, we build on the Ricardian trade model of Eaton and Kortum (2002) to study the effect of improving each U.S. state's local agricultural productivity—a necessary policy to promote the consumption of local agriculture—on consumer welfare.

Our general equilibrium application allows us to create counterfactuals that simulate policy implications and climate-induced production shocks. Our first counterfactual simulates an extreme scenario in which trade is shut down such that each U.S. state is forced to rely on local agriculture. While unrealistic, our autarky counterfactual provides evidence about the mechanisms through which local agriculture benefits consumers in each state. Then, we run two more simulations to study the effects of improving local agricultural productivity on welfare and resilience against weather shocks. The former simulation allows us to further investigate the mechanisms through which each policy improves consumers' welfare, and the latter simulation is concerned with food security. To assess the distribution of impacts, we construct a ranking of relative comparative advantage based on trade flows and compare the implications of improvements in local agricultural productivity with enhancements of food supply chains. We find unambiguous evidence that improvements in local agricultural productivity is a regressive policy, in the sense that it disproportionately benefits the largest agricultural producers. In contrast, a policy that enhances food supply chains between U.S. states is progressive, since it benefits net importers.

This article makes three primary contributions to the literature on food security and trade. First, our approach is based on a comprehensive but simple model of the U.S. market of crops that can be employed to analyze a large array of counterfactuals concerning food security in the U.S. Our approach accounts for the heterogeneity of farmers' technology through producer specific efficiency terms. We also account for intermediate inputs that come from other farms and are often neglected in other agricultural studies. In addition, we recognize food processors as the main consumers of farmers' production and isolate their substitution effect. By simulating consumer and producer interaction through crop prices, we are able to account for substitution behavior and avoid biases that arise in partial equilibrium analyses.

Secondly, we construct a ranking of relative comparative advantage using our trade data to analyze equity. While most Ricardian trade studies recognize competitiveness (if exporter) and openness (if importer) in their applications, researchers do not exploit the ranking and rather focus on the decomposition. For example, the canonical formulation of Eaton and Kortum (2002) uses the openness terms to infer countries' willingness to trade, but more recently, Keller et al. (2017) uses the competitiveness terms to study technological spillovers in China. We recognize the quality of the ranking as relative comparative advantage in the system and use it to define whether a policy is regressive or progressive. Due to the challenges associated with collecting domestic trade data, our final contribution is concerned with the expanding literature of trade analyses in domestic settings. Since domestic trade mimics a frictionless market, focusing on domestic trade presents the opportunity to study market mechanisms that govern trade and welfare distributions. We decompose each U.S. state's comparative advantage into an agricultural capacity term and a labor expenses term. 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.

This paper is organized as follows. The next section reviews the formulation of Eaton and Kortum (2002), 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. Then, we estimate the model parameters necessary for our post-estimation simulations. The final subsection is interested with our decomposition of each state's comparative advantage. In section 4, we discuss our simulation strategy and results from our counterfactuals. Finally, we offer concluding remarks in section 5.

2 A Ricardian trade model of U.S. crop producers

Our conceptual framework is derived from the Ricardian trade model developed by Eaton and Kortum (2002) and considers the two sides of the market. On the one hand, farmers are crop producers. We 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.[3] We capture their heterogeneity with a state efficiency term denoted as z_i and expenses per harvested acre denoted as c_i.[4] We 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.[5] 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):[6]

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

Efficiency is assumed to be drawn from a Fréchet probability distribution function: $F_i(z) = e^{-T_i z^{-\theta}}$. 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 efficiency outcome, z_i, increases. We refer to T_i as agricultural capacity. The parameter $\theta > 1$ is

[3]In the U.S., a vast tradition of economics studies evidence the heterogeneity of farmers' responses to weather events. 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.

[4]We build on the convention of Reimer and Li (2010) and identify land as the main production input. Because our interest is to decompose comparative advantage into a productivity and production cost term, we do not consider land rents as the main input cost. This is because our empirical strategy to recover θ differs from that of Reimer and Li (2010) that relies on cash rents determining export differentials (see Figure B.1 panel (b)). We instead follow an approach proposed in the canonical specification of Eaton and Kortum (2002) that relies on production costs that determine comparative advantage. For this reason, we rely on expenses per harvested acre. In next section we show that our θ estimate falls close to the small range of the estimations of Reimer and Li (2010).

[5]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.

[6]The constant returns to scale technology assumption refers to the condition in which output prices reflect production processes such as in Equation (1). Figure A.1 shows significant trade flows between all U.S. states, suggesting that no single state (or producer within the state) is a monopoly. Thus, the constant returns to scale assumption guarantees a closed-form solution.

common across producers and influences the likelihood of few states to have comparative advantage within the economy. As θ tends to infinity, the probability of a region having a single region dominating the market decreases.[7] 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 advantage across all producers.

In turn, crop consumers are denoted as j, and we 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, we 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, $\Phi_j = \sum_i^I T_i(c_i t_{ij})^{-\theta}$, where I dennotes all producers, 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 $\gamma = \Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)$, and Γ is the gamma function:

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

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

[7] Assuming that climate change will increase yield variability through the increase in the probability of climate shocks, Reimer and Li (2009) exploit θ to study how yield variability will affect prices and welfare across countries. In contrast to their approach, we study short run variations in efficiency that are region specific, so we instead shock the parameters T_i to simulate welfare losses such as those caused by droughts, floods and early frost.

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 $X_j = \sum_i^I X_{ij}$ be expenditure on commodities from all regions, where X_{ij} is trade going from i to 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):

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

Equation (4) has two empirical properties regarding short-run substitution behavior in the face of extreme weather events.[8] 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.[9] Both responses are consistent with a consumer substituting from one source to another as depicted in Equation (2).

Because crop production combines several inputs, we 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 $c_i = w_i^{\beta} p_i^{1-\beta}$.[10] Here, w_i is labor ex-

[8]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 value of T_j. And, $\frac{\partial \pi_{ij}}{\partial T_i} > 0$, or there is a positive relationship between the expenditure on goods from i and the value of T_i.

[9]Dall'Erba et al. (2021) provide evidence of producers substituting domestic intermediate inputs for imports when a state is impacted by drought events. Because trade is endogenous and as shown in Equation (4) depends on producers' characteristics, econometric models that analyze producers' outcomes with trade variables cannot interpret the coefficient associated with the imports variable as causal. To address the endogeneity concerns, the authors exploit two strings of the literature discussed here. First, a gravity-equation is employed in a first-stage. Then, the predicted imports variable from the first-stage is recovered and employed on the second-stage to analyze U.S. farmers' profits.

[10]Wang et al. (2015) find that the U.S. agricultural sector increased its consumption of intermediate

penses per harvested acre and p_i is defined as in Equation (3) and illustrates that farmers buy inputs from other farms. In addition, we normalize Equation (4) by multiplying it by domestic sales, $(\frac{X_j}{X_{jj}})$, and thus obtain 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):

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

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

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.[11]

Equation (6) is a gravity-like equation commonly found in the trade literature, where the expressions in parentheses are the size terms.[12] 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.

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inputs by 140% from 1948 to 2011. The authors attribute the increase to a decline in prices of other inputs. In their Ricardian trade application, Reimer and Li (2010) do not account for intermediate inputs, but their analysis is at the international level. In contrast to their approach, we include intermediate inputs both in the estimation of our structural parameters and our simulations. We demonstrate analytically and empirically that the inclusion of intermediate inputs significantly affects results in the U.S. domestic trade setting.

[11]Notice that if no intermediate inputs are used, i.e., $(1-\beta) = 0$, the dependent variable is simplified into $\ln X_{ij}$ and $\ln X_{jj}$. In the next section, we demonstrate that neglecting the intermediate inputs adds additional measurement error to our estimation.

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

3 Empirical Strategy

The previous section describes our mathematical conceptual framework of U.S. crop producers. We incorporate assumptions about the heterogeneity of farmers' production, and their use of intermediate inputs and derive realistic behavior for the economic agents. In this section, we first discuss the data employed in our analysis and how we process our data to avoid threats to our empirical strategy. Then, we employ the data to recover the necessary structural parameter to run our simulations in a two-step approach. Across both sub-sections, we empirically test some implications of our mathematical model to provide evidence about the internal validity of our approach. The final sub-section studies the relative comparative advantage of U.S. states in the domestic market of crops.

3.1 Data

U.S. crop markets are comprised of 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, ranchers 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 determined at the international level. Food processors' demand for domestic crops is derived from 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, we drop foreign imports and exports and instead just focus on domestic trade flows, excluding animal feed grains. The concern of this practice is that we are focusing on a small subset of crop production. Figure 1 describes the consumption of the three crop categories considered here as classified by the Standard Classification of Transported Goods (SCTG). Crops destined 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, our analysis focuses on the largest aggregation of crops: U.S. farmers' crop production destined for human consumption within the U.S.

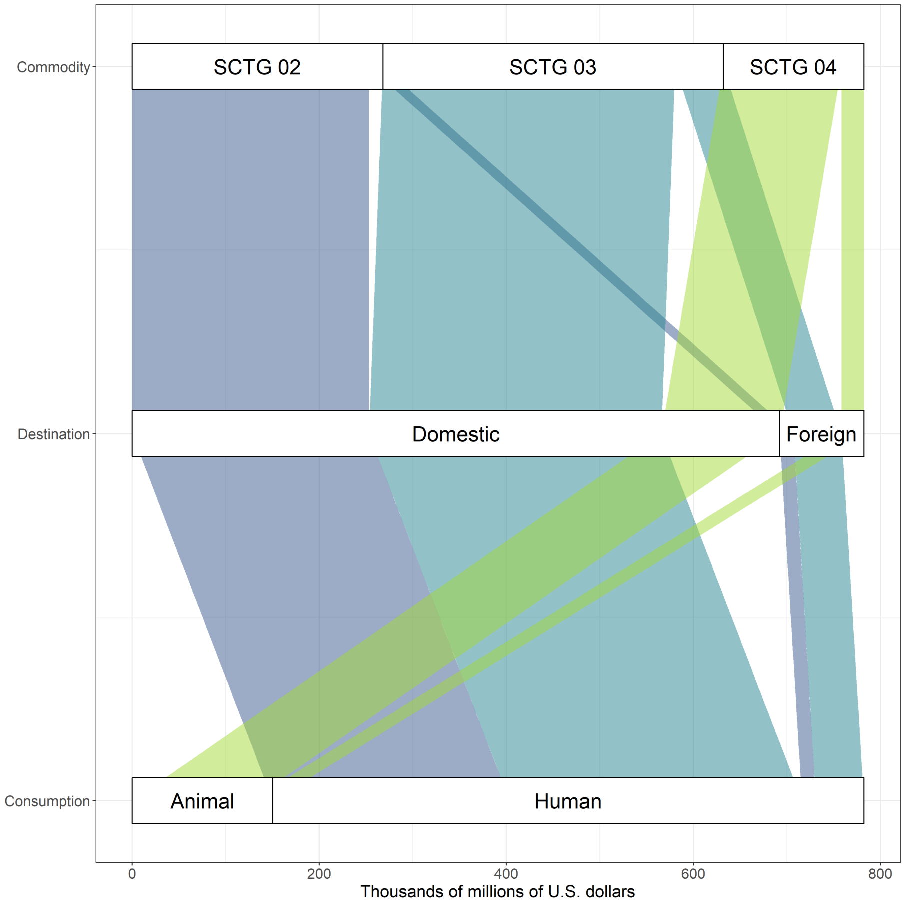


Figure 1: Consumption of U.S. crop production.
Note: SCTG 02 includes cereals such as wheat, corn and rye. SCTG 03 includes fruits and vegetables. SCTG 04 includes cereals for animal consumption. Only SCTG 02 and SCTG 03 corresponds to human consumption. Analysis focuses on domestic consumption of crops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

Our 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 employs the USDA Census of Agriculture. Our 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.

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 distance and whether two states share the same border. We calculate distance between polygons' centroids in a shapefile, using the Geoda software. Our measure of distance is in kilometers. The bottom part of the table describes monadic variables that capture attributes specific to individual states. Imports and exports are created using FAF4 data to describe trade flows. Both measures are in millions of 2017 U.S. dollars. Population density is 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. 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).

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. The value of 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.

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 U.S. Next, metropolitan and highly populated counties are dropped.[13] 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.

Using our trade data, we plot the structural relationships in Equation (6). In Figure B.1, we 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 are observed, agricultural capacity, T_k, is not directly observed. We 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). In the next part, we recover the structural parameters in Equation (6), using the data discussed in this part.

3.2 Recovering structural parameters

Recovering the structural parameters θ and T_i 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. In our notation, we keep the hypothesized sign, since the estimated coefficients should conform with the direction of the sign. 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) and are denoted as $\hat{S}_i$ and $\hat{S}_j$ for the exporter and the importer

[13] The cutoff at the county level is 1,600.

respectively. In contrast with Equation (7), θ can be recovered from Equation (8) since it is associated with an observable variable. Here, ν_k is the error term. Our 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.[14]

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

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

The estimation of Equation (7) is carried out through the use of dummy variables. Since bilateral trade costs are not observed, we approximate them by 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]. 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 (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, we estimate Equation (7) by Feasible Generalized Least Squares (FGLS) estimator.

Figure 2 reports estimates from Equation (7). In panel (a), we 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

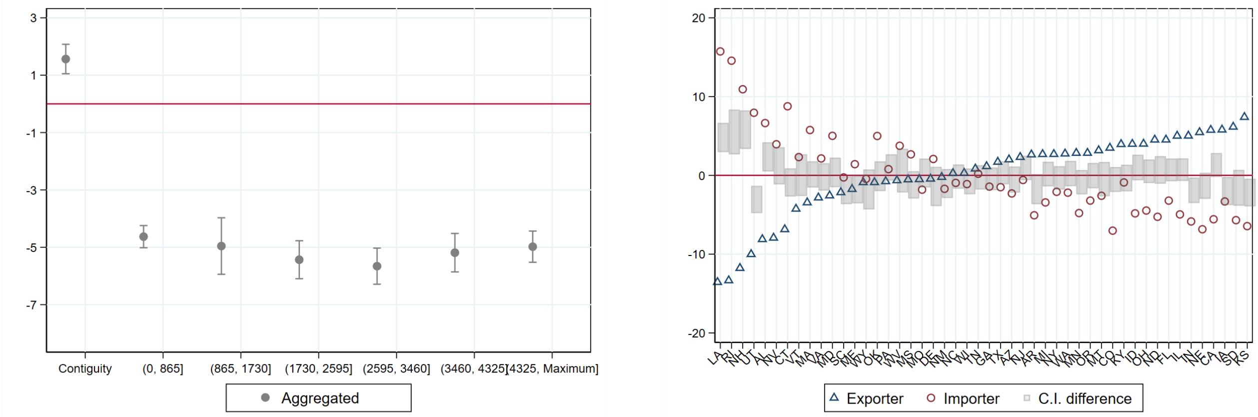
[14] We consider $\beta = 0.12$, the weighted average of our crop aggregation, despite that SCTG 03 is more labor intensive than SCTG 02. For robustness, we test $\beta \epsilon [.08, .19]$ in Figure C.1 where 0.08 is the share of labor expenses for SCTG 02 and 0.19 is the share of labor expenses for SCTG 03. Results remain equivalent in significance and magnitude within the interval. In Figure C.1, we also test the implications of assuming no intermediate inputs for the U.S. market of crops. As $(1 - \beta)$ decreases i.e., the value of β increases, θ attenuates. This implies that not accounting for intermediate inputs adds error to the dependent variable and attenuates estimations. This is not the case for Reimer and Li (2010) since they employ a different strategy to recover θ.

supported an inverse relationship between trade and distance. Our results indicate that the cost of transporting crops increases with distance, but transportation costs flatten for the last two distance bins. We 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, we estimate Equation (7) by differentiating trade by freight mode. Not only does the U-shape relationship disappear, but as expected, trade decreases with distance.[15]

In panel (b), estimates of the fixed effects 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. 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 confidence interval corresponding to the test of whether each pair is equal to each other is represented in the gray bars. Deviations from symmetry are observed for Louisiana, Rhode Island, New Hampshire and Utah, but symmetry remains for all other states.

Using estimates for the size terms, we estimate the reduced form, Equation (8), 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 labor expenses per acre to be associated with high levels of agricultural capacity, we employ the 2-Stage Least Squares (2SLS)

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



(a) Bilateral trade costs

(b) Size terms

Figure 2: 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 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 confidence interval for the whether each pair is equal to each other is represented in the gray bars.

estimator. Our instrumental variable is average population density in rural counties within each U.S. state. Our construction of population density variable ensures that our instrument affects labor expenses per acre, but not other determinants of agricultural capacity such as climate.[16]

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.[17] Our 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

[16]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 labor expenses per harvested acre (Liang et al., 2017).

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

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 our instrument is not a weak one.[18]

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 θ. Values in parentheses are robust standard errors. Coefficients for climate variables are recovered up to the constant $\frac{1}{\beta}$; *p < 0.10; **p < 0.05, ***p < 0.01.

Next, we test the robustness of our selection of intermediate inputs. We repeat the process discussed in this section but with different values for β, starting from 1 and decreasing by .01 until reaching 0. We first recalculate the dependent variable in Equation (7), and then we recover and re-estimate Equation (8). This exercise allows us to study the robustness of our selection of β and the implications of assuming no intermediate inputs in the estimation of θ. Figure C.1 shows our results.

[18]A concern associated with the estimations in Table 2 is the finite sample properties of the IV estimator (Heid et al., 2017). 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. We implement their estimator and find no difference with the estimations in Table 2.

Panel (a) focuses on the exporter size-term, while Panel (b) focuses on importer size-term. In our study, we consider $\beta = 0.12$, the weighted average of our crop aggregation, despite that SCTG 03 (0.19) is more labor intensive than SCTG 02 (0.08). Results remain equivalent across $\beta \epsilon [.08, .19]$ and are indicated by the solid vertical lines. The horizontal dashed line is our estimates from Table 2. This exercises also demonstrates that our estimate of θ is independent to an arbitrary selection of intermediate inputs within the interval of $[.08, .19]$. Figure C.1 also shows that as β approaches zero, estimation becomes upwardly biased and imprecise. However, as the selection of intermediate inputs increases i.e., $(1 - \beta)$ approaches zero, the estimated θ attenuates. This is likely an artifact of measurement error.

To our 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, we rely on the work of Reimer and Li (2010) to further test the robustness of our estimate. 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. Additionally, Reimer and Li (2010) report that their lowest $\theta = 2.52$ uses maximum likelihood and a parametrization of the Fréchet distribution. 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. Therefore, our importer side estimate of $\theta = 2.468$ falls slightly below the small range of valid estimates found by Reimer and Li (2010). We choose $\theta = 2.486$ as our preferred value for comparative advantage because it is closer to those found in their study.

3.3 Comparative advantage

To analyze the comparative advantage of each U.S. state, Equation (8) is re-arranged into the following equality: $\hat{T}_i = (e^{\hat{S}_i} w_i^{\theta})^{\beta}$. Using labor expenses per harvested acre, the estimates for the exporters' size term, our preferred value for $\theta = 2.468$, and $\beta = 0.12$, we calculate 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 3.

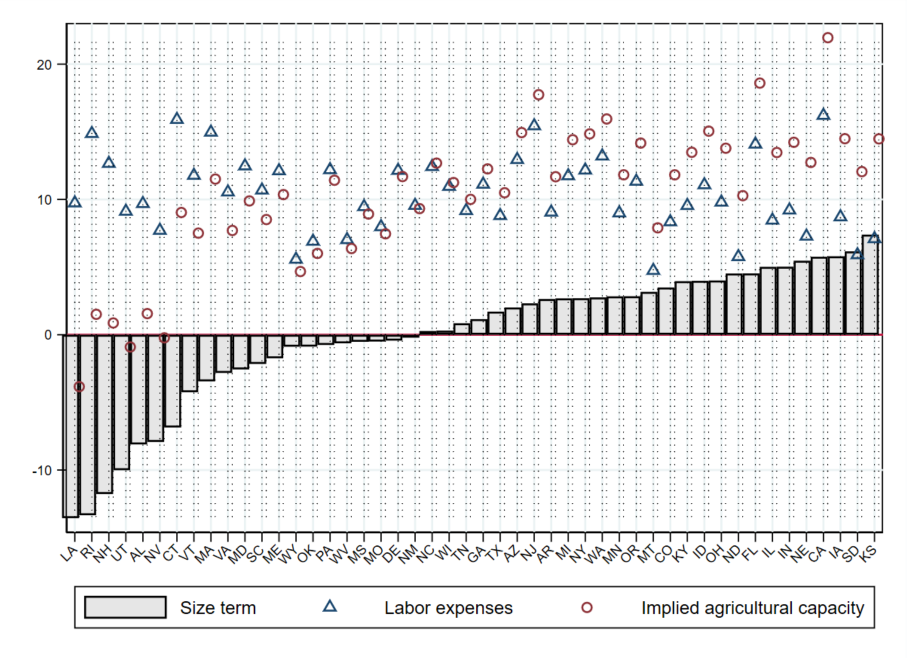


Figure 3: Comparative advantage (exporter size-term) decomposition.
Note: Figure reports size terms estimates obtained using Equation (8): natural log of the implied level of agricultural capacity and natural log of labor expenses per harvested acre in each U.S. state multiplied by $\theta = 2.468$. 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 3 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.

Our results indicate that Kansas, South Dakota, Iowa, California, Nebraska, Indiana, Illinois and Florida have a comparative advantage in the U.S. market of crops. 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 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, we employ the structural parameter for comparative advantage and our trade data to run three simulations. First, we run an autarky simulation such that inter-state trade is shut down. Results from this simulation serve two purposes. First, they highlight the importance of accounting for intermediate inputs in welfare analyses. Secondly, autarky simulation results represent the extreme-case scenario in which U.S. states are forced to rely on local agriculture. The second simulation is interested with welfare benefits from a policy that promotes local agriculture by improving local agricultural productivity in comparison to an opposing policy recommendation that promotes trade by enhancing food supply chains. The purpose of this simulation is also two-fold. We trace back benefits from improvements in local agricultural productivity to the relative comparative advantage in Figure 3 to show that a local agriculture policy is regressive. We also decompose the results to study the mechanisms through which each policy recommendation improves welfare. The final simulation studies a recovery scenario in which U.S. states are impacted by extreme weather events and state officials pursue a local or trade policy. This simulation is concerned with resilience against weather shocks.

4 Discussion of Welfare and Resilience Simulations

Our welfare measure is given by changes in real expenditure on crops. Our comparative advantage parameter (i.e., $\theta = 2.468$) and our trade data (i.e., Table 1) are sufficient statistics to run our welfare analyses (Arkolakis et al., 2012; Baier et al., 2019). A region's income can be obtained 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, we define an equilibrium measure in changes in the structural parameters, given in Equation (10):

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

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

Finally, we 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 account for 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 our final expression of welfare given by Equation (11), where $\hat{W}_i$ is the change of welfare in i:[19]

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

Contrary to the Ricardian trade application on agriculture of Reimer and Li (2010), we consider intermediate input consumption. As our expression of welfare suggests, the larger the share of intermediate inputs $(1 - \beta)$, the higher the welfare effect. This is because production shocks not only hinder production in the region, but will cause disruptions in the production of other regions further magnifying the welfare effect.

Equilibrium deviations caused by weather events and food policy implementations can

[19]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.

be analyzed using Equation (10) and Equation (11). We 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 of increasing T_i. Finally, enhancements of food supply chains between U.S. states are simulated by reductions in t_{ij} for all states.

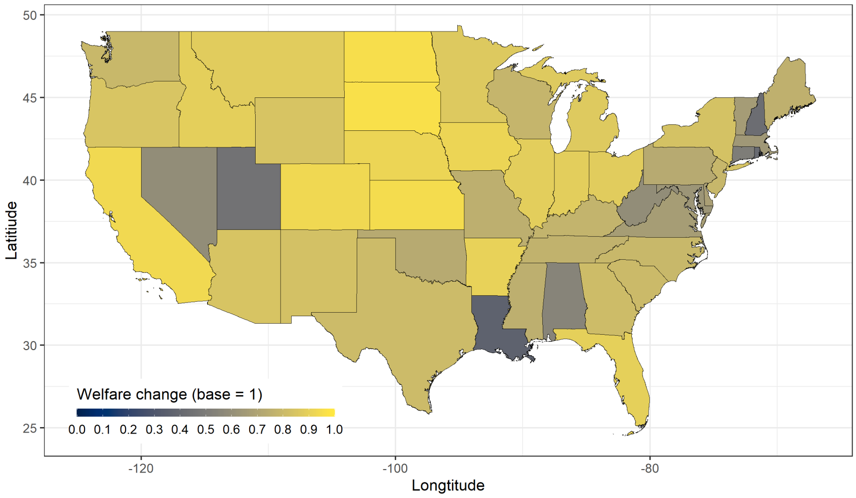
4.1 Autarky

We first simulate an autarky setting in which inter-state trade is shut down. Results from this simulation serve two purposes. First, they highlight the importance of accounting for intermediate inputs in welfare analyses in a Ricardian setting. Secondly, autarky simulation results represent the extreme-case scenario of a situation in which states are forced to rely on local agriculture. 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 (12):

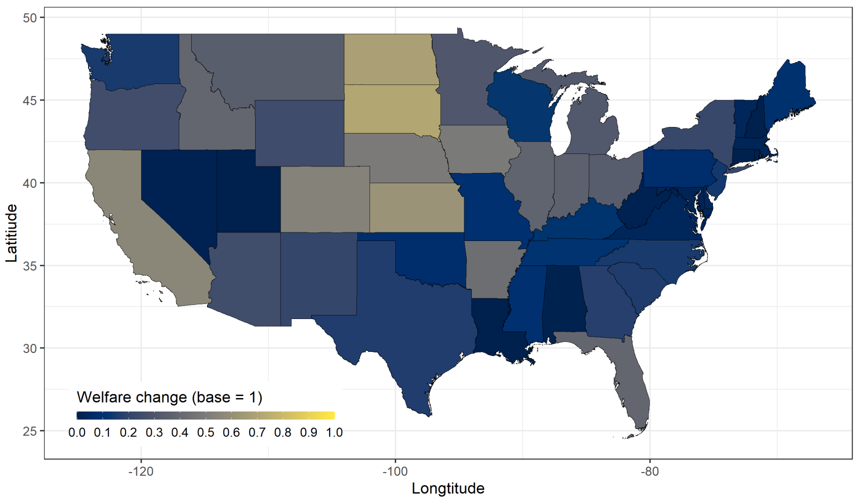
$$\hat{W}_i^A = \pi_{jj}^{\frac{1}{\theta\beta}}. \tag{12}$$

This intuitive result illustrates that the higher the reliance on imports is, the higher the loss when the level of imports is reduced. The results of our counterfactual simulations show large losses associated with a movement to autarky. Figure 4 illustrates the spatial distribution of our results.

To demonstrate the role of intermediate inputs in our approach, we conduct two versions of the autarky simulation: one in which labor is the only input (Panel a), and one that accounts for intermediate inputs (Panel b). The inclusion of intermediate inputs amplifies the welfare losses in our simulation. For the comparable case (Panel (a)), Reimer and Li (2010) report welfare losses ranging from 0% to 5.5% at the international level, while we find a larger range from 4% to 64%, with a national welfare loss of 24%. We attribute the difference to the large trade dynamics in the U.S. market of crops as suggested by Figure A.1. Accounting for intermediate inputs, autarky in the U.S. produces a 79% average welfare loss. The results of our autarky counterfactuals not only provide evidence that the exclusion of intermediate inputs underestimate welfare results, but also illustrate how integrated the U.S. domestic market of crops is relative to the international setting of Reimer and Li (2010). In our domestic setting with no trade barriers, states specialized their agricultural production but also states with appropriate agricultural capacity become food exporters, while states with low agricultural capacity become food importers.



(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 4: Autarky simulation results.

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 by 98%. Similarly, Illinois consumes 75% of its crop expenditure domestically, but its welfare loss rises from 11% to 63% after accounting for intermediate inputs. 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, 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.

Figure 5 shows a scatterplot relating the welfare impacts from the autarky simulations in Figure 4 with the size term estimates shown in Figure 3. Here, the relationship in triangles considers no intermediate inputs, but the relationship in circles does. Because the interpretation of the size term estimates is relative comparative advantage, the positive relationship between welfare losses from shutting interstate trade and the size term suggest that a policy that promotes local agriculture may be regressive. While shutting down trade is the extreme and sudden scenario, autarky results indicate large agricultural producers can substitute imports for local production easier than net importers. In fact, our simulation results indicate that several states will decrease their welfare to almost zero if intermediate inputs are accounted.

4.2 Welfare-induced food policy

Clapp (2015) urges action on promoting food consumption from local sources due to the multifaceted consequences of specialized food production. Several layers separate food consumers and producers that take the form of financial tools, bargaining power, and awareness of environmental and labor impacts. These layers impede the creation of sustainable production of foods that are healthy for consumers and support rural communities (DuPuis and Goodman, 2005; Levkoe, 2011; Marsden, 2013). Even recently

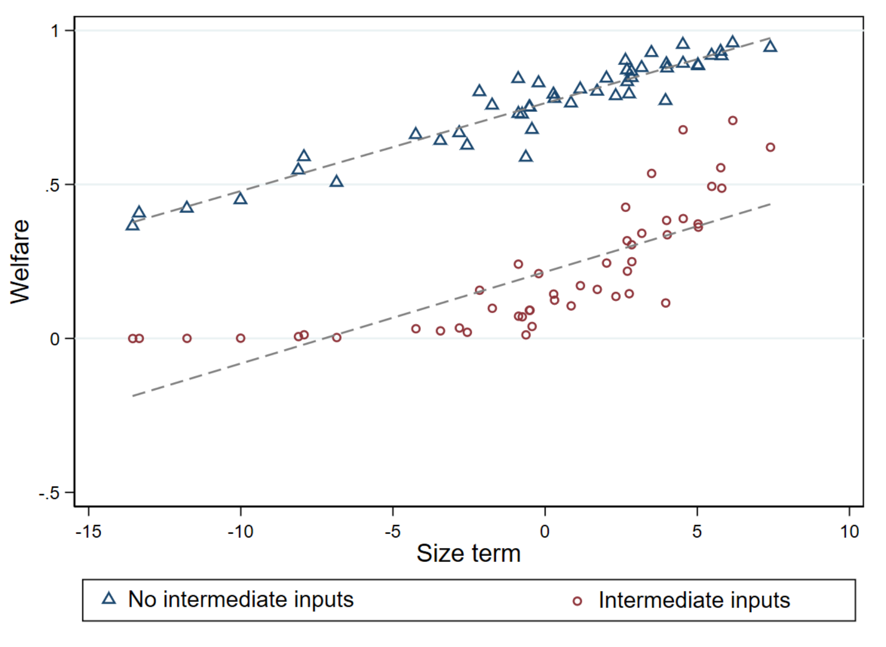
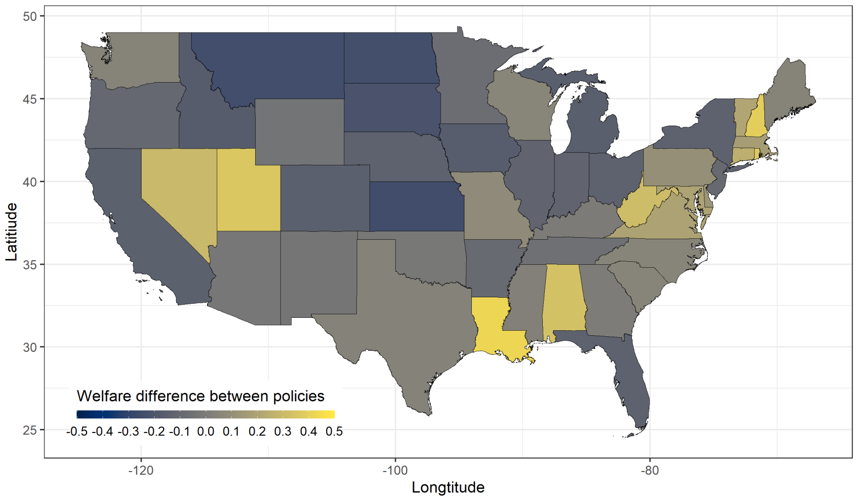


Figure 5: Autarky welfare impacts, and comparative advantage (exporter size-term).
Note: Figure shows a scatterplot relating welfare impacts from two autarky simulations, where the relationship in triangles considers no intermediate inputs and the relationship in circles does, with size term estimates from the estimation of Equation (8). The direction of the relationship is positive and implies that the higher the relative comparative advantage on the market of crops, the more resilient the state is to a complete shut down of trade.

in the face of COVID-19, distant food sources caused misallocation of resources that increased food prices and food waste (Hobbs, 2020; Thilmany et al., 2020). Nevertheless, the concern of promoting food consumption from local sources in a uniform manner is opportunity-cost of alternative food policies that become specially important with the raise of food insecurity in the U.S. Here, we cast some light to this concern by simulating the impact of improving local agriculture on consumer welfare and then contrasting these results to those from an opposing policy recommendation that aims to reduce the cost of trade. Our results can inform policy makers about the suitability of the state to benefit from the promotion of local agriculture.

Both improvements in local agricultural productivity and enhancements in food supply chains lead to welfare gains for consumers. By themselves, welfare results for each policy counterfactual offers a basis for comparison 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 expenditures on consumption of commodities from other regions 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. Comparing both opposing policy recommendations provides insights of what policy achieves the highest benefits for consumers and why. We 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. We simulate each state's change in productivity or trade costs separately to control for spillovers from other states. Figure 6 illustrates our 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 compared to a food policy that improves local agricultural productivity.

On average, U.S. consumers' welfare is 13% higher under the scenario of reducing trade costs than under improvements of local agricultural productivity. As expected, the average expenditure increases and the level of prices decreases under a policy that promotes local agriculture. Both policies 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, the distribution of welfare impacts across states demonstrates that the policies have differential impacts for different regions. 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.

We also study the equity implications of each type of policy. Figure 7 shows a scatterplot relating the welfare impacts from our welfare simulations in Figure 6 with the size term estimates shown in Figure 3. Here, the relationship in triangles represents local policy-induced welfare gains, and the relationship in circles represents trade policy-induced welfare gains. Because the interpretation of the size term estimates is relative comparative advantage, the darker relationship suggests that a policy that promotes local agriculture may be regressive. On the other hand, the lighter relationship suggests that a policy that promotes trade through enhancements of food supply chains may be progressive. While each type of welfare impact is not comparable since their baseline differ from state to state, they indicate a clear trend of who benefits from each type of policy. Promotion of local agriculture in states with low comparative advantage is not a policy to pursue if the interest of policymakers is to promote consumers' welfare in such states.

To further explore the mechanisms and welfare distributions caused by the two food policies, Figure 8 presents a boxplot analysis for each policy's impact on expenditure and prices respectively. 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

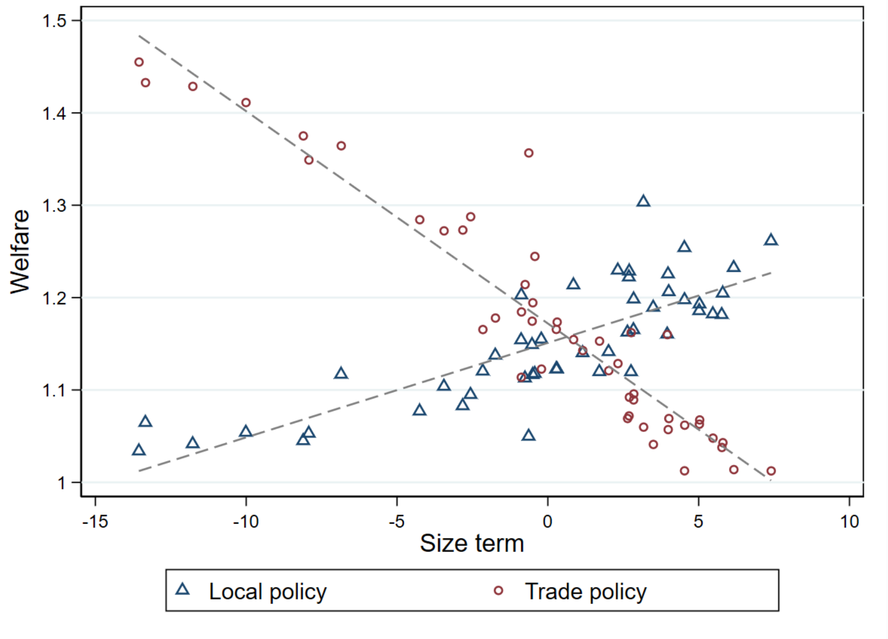


Figure 7: Welfare impacts from a local and trade policy, and comparative advantage (exporter size-term).
Note: Figure shows a scatterplot relating welfare impacts from local improvements of agricultural productivity (triangles) and enhancements of food supply chains (circles) with the size term estimates from the estimation of Equation (8). The direction of the relationship in triangles is positive, suggesting local improvements of agricultural productivity may be regressive. The direction of the relationship in circles is negative, suggesting enhancements of food supply chains may be progressive.

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.

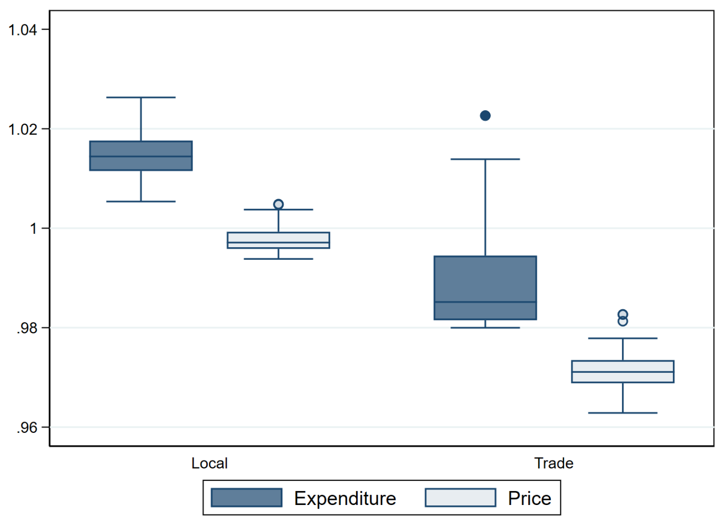


Figure 8: Welfare distribution analysis.

The relative gains illustrated in Figure 6 and Figure 8 are driven by states with high comparative advantage that benefit little from enhancements of food supply chains between states. Secondly, solving Equation (11) for prices and expenditures is feasible, because there are as many equalities as unknown variables, but this is infeasible with our measure of resilience depicted in Equation (13) 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.

4.3 Resilience against weather shocks

A major concern of having regions relying on local agricultural production is food vulnerability caused by extreme weather events. For instance, farmworkers living in Northern California saw themselves unemployed after the state was severely impacted by a five years drought, raising concerns about food security in the region (Rodriguez et al., 2015; Tortajada et al., 2017). The mechanisms can be characterized as a reliance on few food sources, including local ones. In fact, the work of Burgess and Donaldson (2010) found causal evidence that when regions are connected, famines decreased. But the opposing side is also true specially when regions become highly dependent on food imports (Puma et al., 2015; Gephart et al., 2016). Thus, there must be an appropriate middle point between relying on local and foreign sources to deal with production shocks such as those caused by extreme weather events. In this section, we cast some light to this question for U.S. states. We simulate how each U.S. state is impacted by an extreme weather event and then how a local or a trade policy can help the state recover. Because the climate-induced welfare losses will depend on the composition of the state's food sources, we run two more simulations where the main two food produces are impacted to study the role of import-dependency on resilience.

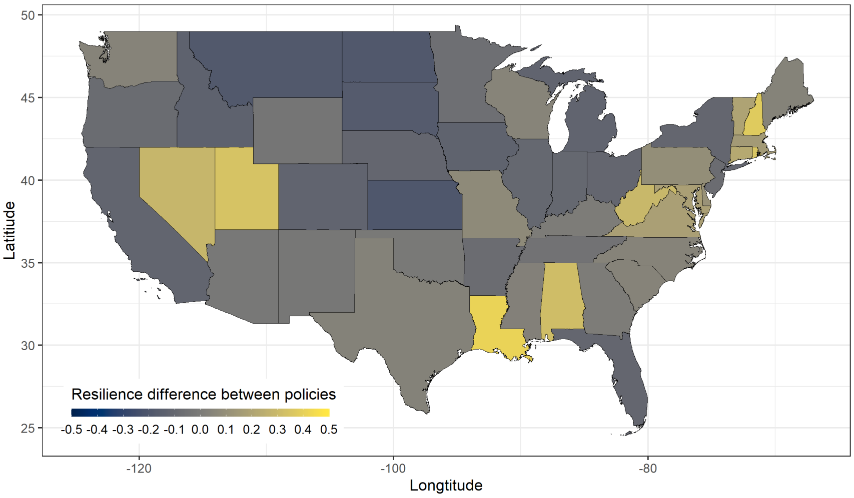
We use Equation (11) to construct each state's recovery path. This exercise can inform policy makers about the resilience potential of each food policy. Equation (13) describes our measure of the effectiveness of policy responses to mitigating the effects of a negative production shock, where R_i^{policy} measures the difference between the welfare impacts of the shock and the policy response. Here, $\hat{W}_i^{shock}$ is the state's welfare reduction caused by the weather shock. The shock is simulated by a reduction of T_k by 5%. $\hat{W}_i^{policy}$ is the bounce back after the implementation of the food policy and is simulated as in the previous section.

$$R_i^{policy} = \hat{W}_i^{policy} - \hat{W}_i^{shock}. \tag{13}$$

We evaluate both opposing food policies as a response to each type of weather event. First, we focus on local weather shocks. Then, we 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.[20] 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 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 8 suggest that the large difference is driven by these states that benefit little from a local agriculture policy but significantly from a trade policy.

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

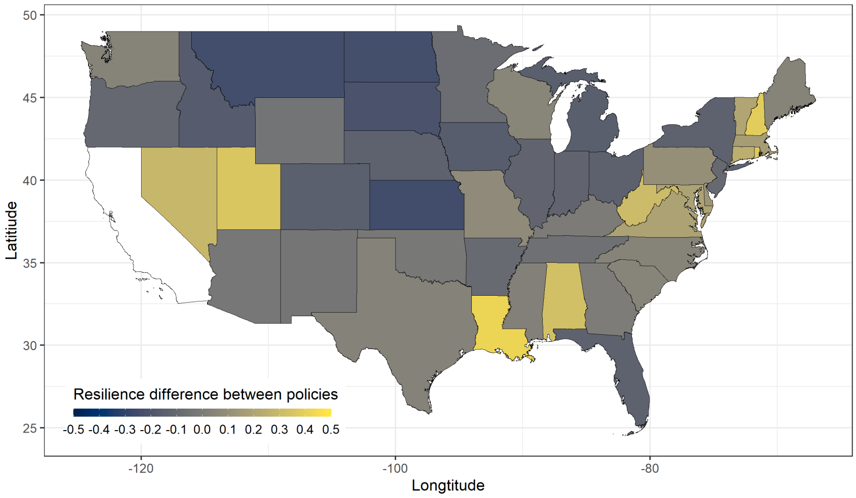


	Local				Trade			
	Mean	(S.D.)	Minimum	Maximum	Mean	(S.D.)	Minimum	Maximum
$\hat{R}_i$	0.12	(0.049)	0.03	0.23	0.16	(0.121)	0.01	0.44

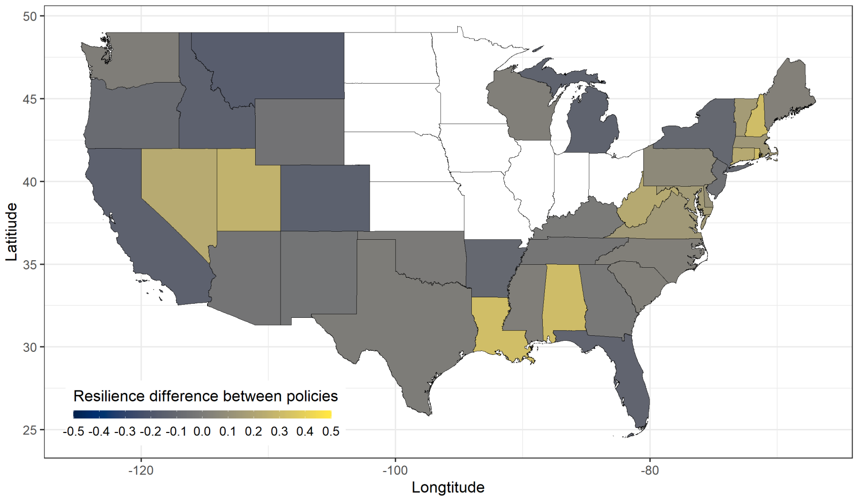
Figure 9: Difference in resilience to local weather shocks from each opposing policy recommendation.

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 compared to a food policy that improves local agricultural productivity.

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 described in Equation (6). 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 compared to a food policy that improves local agricultural productivity.

5 Conclusions

We study the effect of improving each U.S. state's local agricultural productivity on consumers welfare by considering a general equilibrium model of domestic crop trade that accounts for the heterogeneity of farmers' technology and consumers' substitution effects.

Three counterfactuals are considered that provide insights into each policy's implications for prices, consumer expenditures, and welfare in the face of production shocks, which we consider as arising because of extreme weather events. We also construct a ranking of relative comparative advantage in the U.S. market of crops and find unambiguous evidence that improvements in local agricultural productivity may be a regressive policy, since it benefits the largest agricultural producers. In contrast, a policy that enhances food supply chains between U.S. states may be progressive, since it benefits net importers of food.

Our extension of the Ricardian trade model of Eaton and Kortum (2002) is a comprehensive but simple model of the U.S. market of crops that can be employed to analyze a large array of counterfactuals concerning food security in the U.S. The Ricardian trade model of Eaton and Kortum (2002) has been extensively used in international trade analyses, but it is underemployed in domestic settings, despite the profound importance of domestic trade. Thus, our employment of their Ricardian trade model in a domestic setting allows us to study market mechanisms that govern trade and welfare distributions since domestic trade mimics a frictionless market. We demonstrate its capabilities by simulating welfare gains from improvements of each state's agricultural capacity and enhancements of food supply chains between U.S. states with implications to food security. We conclude by re-stating the importance of considering consumer welfare in the promotion of local agriculture. While advocates for local agriculture are concerned about valid health and environmental concerns, not all states are able to rely on local agriculture. In fact, a better food security policy for the large majority of states may be to rely on food imports and instead focus on expanding and improving food supply chains.

References

Anderson, J. E. (1979). A theoretical foundation for the gravity equation. *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.

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.

Blay-Palmer, A., Landman, K., Knezevic, I., Hayhurst, R., et al. (2013). Sustainable local food spaces: constructing communities of food. *Local Environment*, 18(5):521–641.

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.

Clapp, J. (2015). Distant agricultural landscapes. *Sustainability Science*, 10(2):305–316.

Dall'Erba, S., Chen, Z., and Nava, N. J. (2021). The U.S. interstate trade will overcome the negative impact of climate change on agricultural profit. *Forthcoming in the American Journal of Agricultural Economics.*

DuPuis, E. M. and Goodman, D. (2005). Should we go "home" to eat?: Toward a reflexive politics of localism. *Journal of Rural Studies*, 21(3):359–371.

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

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.

Heid, B., Larch, M., and Yotov, Y. (2017). Estimating the effects of non-discriminatory trade policies within structural gravity models. *CESifo Working Paper Series*.

Hobbs, J. E. (2020). Food supply chains during the covid-19 pandemic. *Canadian Journal of Agricultural Economics*.

Keller, W., Santiago, J. A., and Shiue, C. H. (2017). China's domestic trade during the Treaty-Port Era. *Explorations in Economic History*, 63:26–43.

Krugman, P. R. (1981). Intraindustry specialization and the gains from trade. *Journal of Political Economy*, 89(5):959–973.

Levkoe, C. Z. (2011). Towards a transformative food politics. *Local Environment*, 16(7):687–705.

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.

Marsden, T. (2013). Sustainable place-making for sustainability science: The contested case of agri-food and urban–rural relations. *Sustainability Science*, 8(2):213–226.

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. (2009). Yield variability and agricultural trade. *Agricultural and Resource Economics Review*, 38(2):258–270.

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.

Thilmany, D., Canales, E., Low, S. A., and Boys, K. (2020). Local food supply chain dynamics and resilience during COVID-19. *Applied Economic Perspectives and Policy*.

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.

Wang, S. L., Heisey, P., Schimmelpfennig, D., and Ball, V. E. (2015). Agricultural productivity growth in the United States: Measurement, trends, and drivers. *Economic Research Service, Paper No. Err-189.*

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

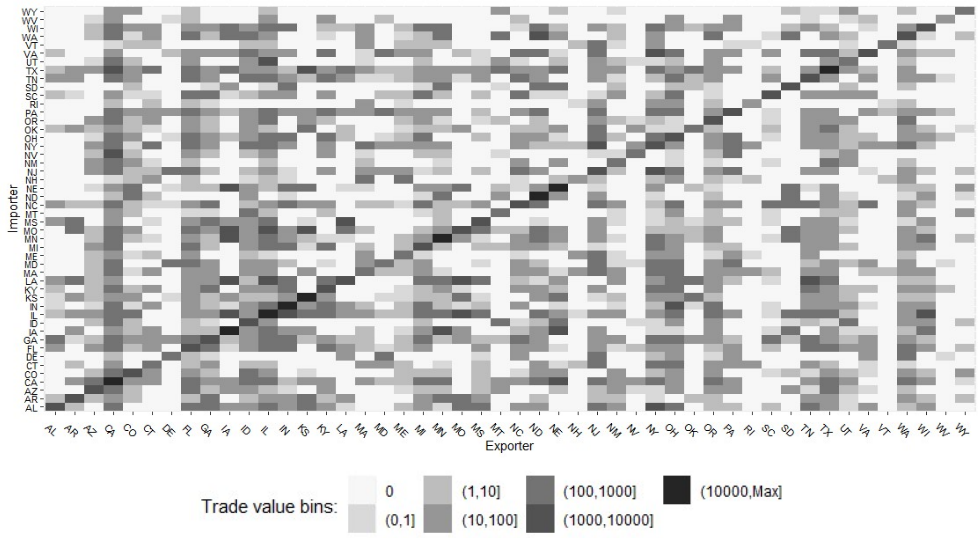
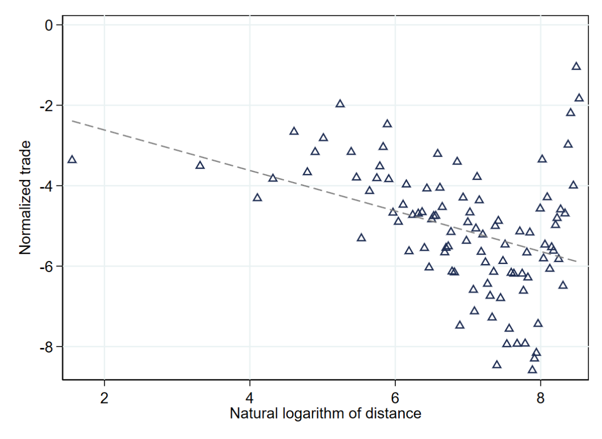


Figure A.1: Origin and destination of U.S. domestic crop consumption.
Note: Heat map of crop trade between all U.S. states. Most crop production is consumed within the state, but significant trade flows exist between all U.S. states. All measure are in millions of 2017 U.S. dollars.

B Relationship between gravity equation and crop data



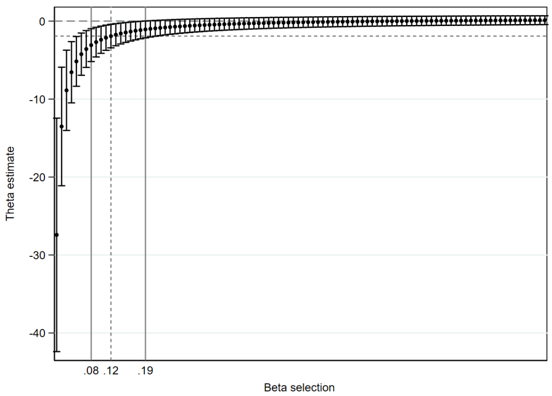
(a) Distance

(b) Cash rents

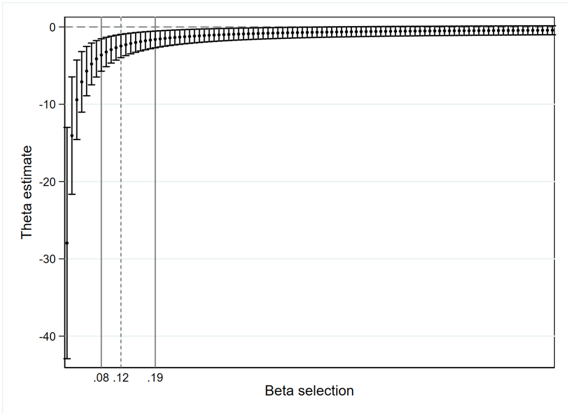
Figure B.1: Relationship between gravity equation and crop data.

Note: Each point is an average of a cluster of observations around it. 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.

C Robustness test of selection of intermediate inputs



(a) Exporter size-term



(b) Importer size-term

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