U.S. Interstate Trade Will Mitigate the Negative Impact of Climate Change on Crop Profit

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According to the current Intergovernmental Panel of Climate Change report, climate change will increase the probability of occurrence of droughts in some areas. Recent contributions at the international level indicate that trade is expected to act as an efficient tool to mitigate the adverse effect of future climate conditions on agriculture. However, no contribution has focused on the similar capacity of trade within any country yet. The U.S. is an obvious choice given that many climate impact studies focus on its agriculture and around 90% of the U.S. crop trade is domestic. Combining a recent state-to-state trade flow dataset with detailed drought records at a fine spatial and temporal resolution, this paper highlights first that trade increases as the destination state experiences more drought and inversely in the origin state. As a result, crop growers' profits depend on both local and trade partners' weather conditions. Projections based on future weather data convert the crop grower's expected loss without trade into expected profit. As such, this paper challenges the estimates of the current climate impact literature and concludes that trade is expected to act as a $14.5 billion mitigation tool in the near future.

Key words: Agricultural profit, drought impact evaluation, intranational trade.

JEL codes: F14, F18, Q52.

Recent decades have witnessed an increase in the frequency and intensity of extreme weather events, and the latest report of the Intergovernmental Panel on Climate Change predicts that this trend should continue in the near future. Agriculture, the economic sector that is the most sensitive to changes in weather conditions, is expected to be greatly affected by such changes, no matter in what country the production takes place (see, for example, Mendelsohn, Nordhaus, and Shaw 1994; Deschênes and Greenstone 2007, for the U.S.; Lippert, Krimly, and Aurbacher 2009; Moore and Lobell 2014, for Europe; Wang et al. 2009, for China). However, several authors have brought to the fore that the international trade of agricultural goods has the capacity to act as a major mechanism for adapting to climate change (Reilly and Hohmann 1993; Rosenzweig and Parry 1994; Schenker 2013).

Trade theory (Helpman and Krugman 1985; Markusen 1995; Feenstra 2015) suggests that current agricultural production choices reflect current differences in local factor endowments (e.g. soil, climate, water access) and that trade takes place based on the current level of complementarity (e.g. crops used for animal feeding) or substitution with local production. However, in the long run, new climate conditions will have the potential to disrupt current comparative advantages, which would lead to changes in production choices and trade patterns. In addition to this long-run change, the expected increase in extreme weather events should result in a higher yield volatility as well.

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Reimer and Li (2010) and Ferguson and Gars (2020) indicate that short-run production losses following a sudden drought or a flood can be substituted with imports (trade creation). For the countries traditionally importing from a place experiencing that sudden drop in production, the shift to other providers (trade diversion) is a viable option too (McCorriston and Sheldon 1991). As a result, trade has the potential tool to mitigate the harmful effects of climate change (Randhir and Hertel 2000).

Yet, it is important to note that the capacity for international trade to cope with expected climate change has been challenged in a recent contribution by Costinot, Donaldson, and Smith (2016). Based on a vast dataset of agricultural productivity, their results show that international trade plays only a minor role in climate mitigation compared to that of domestic production reallocation. Therefore, they expect that new climate conditions will lead crops whose yield has fallen to be relocated within the country or simply imported instead. However, their estimates disregard the role of and changes in domestic trade flows that crop reallocation and new crop prices will induce. This gap is particularly relevant for large countries like the United States, where agricultural land covers a large amount of its territory (around 40% in 2012). Furthermore, only 8.5% of the U.S. agricultural production is exported, and up to 91.2% of its national intermediate and final demands are satisfied by local production (World Input–Output Database 2016). For this reason, it is likely that new climate conditions will bring about large changes to the U.S. domestic agricultural trade.

As such, the first objective of this paper is to assess the degree of sensitivity of domestic crop trade flows to weather conditions—specifically drought.[1] We focus on crops instead of the entire agricultural sector because crop production is more adversely affected by droughts than any other agricultural activity. In addition, although all previous assessments on trade at the international level define climate change as long-term shifts in temperature or precipitation, they miss the role of past drought events as well as the consequences of their future frequency and intensity. The domestic impact of droughts and their spatial externalities have been studied through structural modeling approaches, such as input–output (see, for example, Pérez and Hurlé 2009), computable general equilibrium (Horridge, Madden, and Wittwer 2005), price-endogenous regional programing (Salami, Shahnooshi, and Thomson 2009) and spatial econometrics (Dall'Erba and Domínguez 2016), but never through a gravity model (e.g. Anderson and van Wincoop 2003; Arkolakis, Costinot, and Rodríguez-Clare 2012; Head and Mayer 2014). Indeed, in the gravity literature applied to agriculture the main variable of interest has been the role of international trade agreements (see, among others, Cho, Sheldon, and McCorriston 2002; Sarker and Jayasinghe 2007; Grant and Lambert 2008; Reimer and Li 2010; Jean and Bureau 2016). Domestic trade, on the other hand, has the advantage of mimicking a free trade situation. Hence, its capacity to act as an adaptation tool can be analyzed without worrying about other cofounding factors, such as man-made trade barriers, market structure differences, and domestic agricultural subsidies.

Due to the challenges associated with collecting domestic trade data, few studies focus on U.S. domestic trade. Early exceptions include McCallum (1995), and Anderson and Van Wincoop (2003), whereas more recent ones are Lin, Dang, and Konar (2014); Lin et al. (2019); and Szewerniak, Xu, and Dall'Erba (2016). Yet, none of them focus explicitly on domestic trade flows of crops. As such, this manuscript fills an important gap in the literature. Based on freight analysis framework data (henceforth FAF4), and with detailed drought data measured at a fine spatial and temporal resolution, the results of our gravity application show that drought in the destination state significantly increases the import flows of crops. Moreover, when a drought occurs in the origin state, it reduces its export capacity to other states.

The second objective of this manuscript is to measure how the farmers' profits change as a result of new weather conditions and domestic trade patterns. This second step calls upon the so-called Ricardian model of climate change, which was first introduced by Mendelsohn, Nordhaus, and Shaw (1994) and later extended by Deschênes and Greenstone (2007), to analyze agricultural profit. Compared to a crop production function, the Ricardian approach has the advantage of accounting for various crops and for substitution between crop varieties as climate changes. In this paper, we rely on the panel data approach of Deschênes and Greenstone (2007) and modify it to our case, where crop growers'

[1] In the last decade only, two droughts raised major concerns about food availability in the U.S.: the California drought (Tortajada et al. 2017) over 2012–2017 and the 2012 drought in the Midwest (Ritzel et al. 2013).

profit is regressed on yearly weather fluctuations and a set of fixed effects that account for additional confounding effects. In addition, we extend it to include the fact that crop growers' profits depend also on interstate exports that are in turn affected by drought in the origin and/or destination states. In the absence of such interregional externalities, the nationwide marginal effect of drought on crop grower's profit would be overestimated, which would bias our results and affect any mitigation and/or adaptation strategy based on them.

As usual in the climate impact literature, the last objective consists in using the estimates calibrated on historical data as well as the expected future weather conditions to project future changes in agriculture. Based on future weather data derived from four combinations of global and regional climate models, our forecast predicts that, in the absence of trade, crop growers will experience an \$11.2 billion nationwide loss in the second part of the century. However, that figure turns into a \$3.3 billion gain when trade is included. This striking difference suggests that previous nationwide estimates of the impact of drought on agriculture have failed to capture the mitigating effect of trade by which exporting states increase their profit when importing states experience a drought.

In order to shed new light on the links among droughts, trade, and crop growers' profits within the United States, the next section provides some background information about the interstate crop trade flows and their database, then provides an example that demonstrates their sensitivity to severe drought. Section III describes the theoretical background and divides it into two subsections, one devoted to the gravity model and one to the Ricardian model. Section IV lists the remaining data and their sources. Estimation results, robustness tests, and forecast for the near future are presented in Section V. Finally, Section VI offers some concluding remarks on the capacity of trade to mitigate the impact of climate change on agriculture.

Intranational Trade of Major Crops in the U.S.

Data Sources for Domestic Trade Flows

To our knowledge, the only previous attempt to measure crop shipments across U.S. states was conducted by Fruin, Halbach, and Hill (1990). The authors conducted two nationwide surveys on the interstate movement of five major cereal grains in 1977 and 1985. Their surveys were discontinued in the 1990s due to the publication of the commodity flow survey (CFS). CFS is a shipper-based survey conducted by the U.S. Census Bureau (USCB) and the Bureau of Transportation Statistics (BTS) during the economic census years (years ending in "2" and "7"). It collects basic information regarding freight movement, such as origin, destination, content, size, weight, dollar value, and mode of transportation. Although the earliest CFS data date back to 1993, the procedures and classification criteria used that year have been largely revised in the following surveys. Hence, only the data collected in the surveys completed in 1997, 2002, 2007, and 2012 are comparable and used here.

There are few limitations associated with the CFS. First, even though CFS is part of the Economic Census, it surveys only a portion of shipping establishments (100,000 out of 716,114) and then adjusts the raw data with survey weights to generate the estimates for the actual trade flows. Furthermore, in its public format, CFS does not identify singularly the shipments satisfying domestic versus international demand (e.g. Illinois corn sold to California may be consumed at destination or exported to Asia). In order to fill up these data gaps, the Oak Ridge National Laboratory developed FAF with the support of BTS and the Federal Highway Administration (FHWA).

Currently in its fourth version, FAF provides data that fills the gaps of CFS by relying on various sources, such as the agricultural census and the merchandise trade statistics, and producing origin–destination figures (both in monetary value and actual weights) across the U.S. states, their metropolitan areas, and foreign countries. Even though most of the final demand for agricultural products is in metropolitan areas, intermediate demand that is composed mostly of livestock and food processing and that is much larger than final demand is not. Disaggregation by commodity in the FAF4 uses a two-digit sectoral classification of transported good (SCTG) like the harmonized system for international trade. Among the seven types of agricultural commodity available, we use only *cereal grains* (SCTG 02) and *fruits, vegetables, and oilseeds* (SCTG 03) because they are constrained to the outdoors and thus are more sensitive to drought than livestock and processed food (see the contributions of Lin, Dang, and Konar 2014 and Lin et al. 2019, for a domestic trade network analysis including all food producing and manufacturing sectors). Note that soybean is the only major crop not listed in SCTG 02. It appears in SCTG 03. As a result, it obliges us to consider these two categories jointly in our manuscript even though fruits, vegetables, and oilseeds represent only 36% of all these commodities. Note that we will provide results for each category separately for robustness checks.

A Snapshot of the Domestic Trade Patterns of Crops

Figure 1 presents the interstate trade flows in 2012. The scatterplot shows, for each state, the volume of crop export on the x-axis and the volume of crop import on the y-axis (the dotted lines are averages). The size of the symbols assigned to each state is proportional to the volume of its production of major crops, whereas the shape corresponds to the type of agricultural output (crop, animal or balanced) that is the most produced. We find that California, Illinois, Iowa, Indiana, Minnesota, Missouri, New York, and Nebraska are the "key" players in the interstate trade system (HH quadrant). Most of these states are large crop producers, they also have well-developed food-related industries and a large population. On the other hand, several states with low exports but high imports (LH), such as Texas, Wisconsin, and Georgia, are large livestock producers with relatively small volumes of crop grown locally. The high exports–low imports category (HL) comprises of two types of states: (*a*) the major producers of high-value crops (fruits, vegetables and greenhouse nursery products), such as New Jersey, Florida, and Michigan; and (*b*) the main crop producers that have small population densities, such as Kansas, North Dakota, and South Dakota. Finally, the states in the low export–low import category are usually small states in terms of population and/or arable land area.

Figure 2 are heatmaps describing the 2012 trade patterns of the two SCTG 02 (Panel (a)) and SCTG 03 (Panel (b)) categories used here. Different shades are used in each cell to represent the volume intensity of each pair of bilateral trade flows. The white cells represent zero trade flow. The origin states are on the x-axis, and the destination states are on the y-axis. Two major findings emerge from the heatmaps: first, the largest off-diagonal flows go from the large crop-producing states, such as Iowa, Illinois, and Kansas, to the livestock-producing states, such as Wisconsin, Texas, and Louisiana. This result confirms our expectations that the major driver of domestic crop trade is animal feed. Second, the "key" players identified in figure 1 emerge in the heatmaps too. For instance, Illinois exports mainly corn and soybean to over thirty states, but it also imports various crops from the rest of the country due to its large food manufacturing

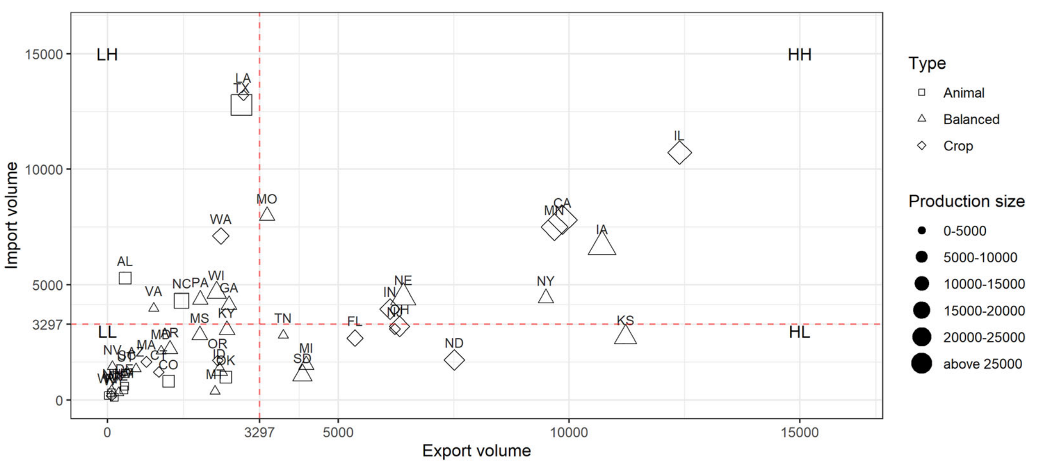

Figure 1. States agricultural production by type

Note: Figure presents the interstate trade flows in 2012. Panel (a) is a scatterplot showing the volume of crop export on the x-axis and the volume of crop import on the y-axis. The size of the symbols assigned to each state is proportional to the volume of its production of major crops, whereas the shape corresponds to the type of agricultural output: animal feeder or crop production. HH panel presents states that are high importers and exporters. LH panel presents states that are high importers but low exporters. LL panel presents states that are low importers and exporters. HL panel presents states that are low importers but high exporters.

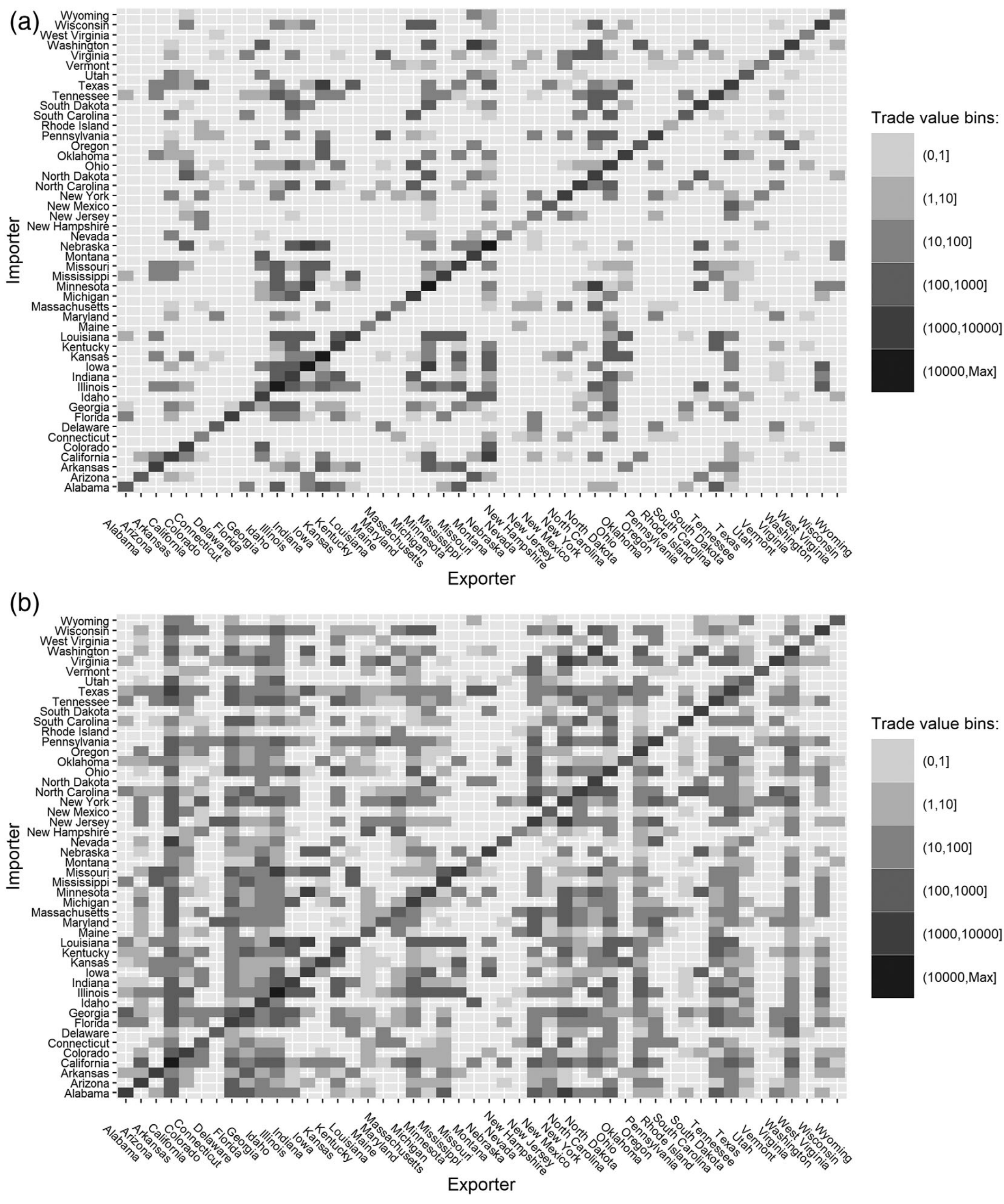

Figure 2. Overview of domestic trade flows between U.S. states

Note: Figure shows heatmaps describing the 2012 trade patterns of animal feeder (Panel (a)) and crop (Panel (b)) production. Different shades are used in each cell to represent the volume intensity of each pair of bilateral trade flows. The white cells represent zero trade flow. The origin states are on the x-axis, and the destination states are on the y-axis.

industry and its specialization in a relatively small number of crops and vegetables.

Changes in Trade Patterns under Severe Drought: The Case Study of Nebraska

The two chord diagrams in figure 3 give us insights about the potential substitution effects caused by a drought. Both figures describe trade flows between Nebraska and its trade partners for the years of 2007 (panel a) and 2012 (panel b). Nebraska was chosen because, according to the recent USDA census, agriculture covers 92% of its land area and contributes to around 30% of its GDP. Nebraska is also the fifth largest producer of cereal grains in the nation.

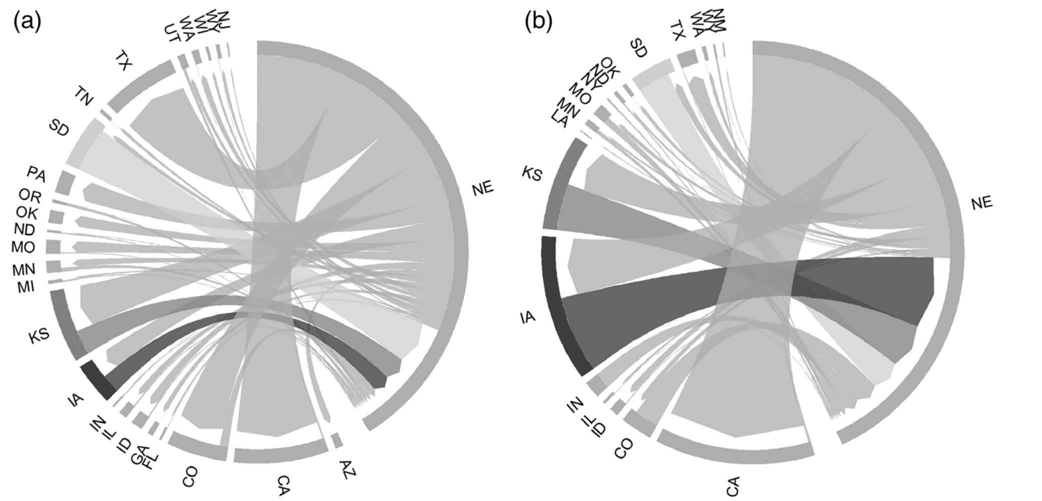

Figure 3. Changes in trade flows under severe drought: Nebraska

Note: Figure shows two chord diagrams that provide insights about the potential substitution effects caused by a drought. Both figures describe trade flows between Nebraska and its trade partners for the year of 2007 (Panel (a)) and 2012 (Panel (b)). Nebraska was chosen because, according to the recent USDA census, agriculture covers 92% of its land area and contributes to around 30% of its GDP. Although Nebraska experienced virtually no drought days in 2007, it was one of the states most affected by the notorious 2012 Midwest drought.

Although Nebraska experienced virtually no drought days in 2007, it was one of the states most affected by the notorious 2012 Midwest drought. We acknowledge that other factors may have played an important role in the observed changes in trade flows, and that only a formal econometric analysis, as described further below, will allow us to identify the singular effect of drought. Yet, several important elements emerge from the 2007 chord diagram: first, the ratio of export to import was 3.29, which indicates that Nebraska was clearly a net crop exporter that year. Second, among the thirty-four states to which Nebraska exported, California, Texas, and Colorado are the main importers while South Dakota, Kansas, and Iowa are at the largest trade partners from which Nebraska imported. In 2012, the ratio of export to import was 1.24. Nebraska exported to just twenty five partners that year, and the total exporting value had dropped by 9%. Nebraska stopped exporting to Pennsylvania, and exports to Texas had decreased by 73% in value. At the same time, the number of importing partners had slightly increased to twenty two, and the total importing value had increased by 107%. The most drastic change from 2007 was the 362% increase in imports from Iowa.

In summary, a local drought seems to reduce exports and increase imports, as common knowledge would suggest. However, neither common knowledge nor the descriptive statistics used so far can tell us if the effects can be generalized to the entire U.S., or if they are statistically significant. The gravity model we use to formally test these hypotheses is described in the next section.

Empirical Strategy

This section breaks down the integrated methodology into two steps. The first step consists of approximating the terms in a gravity model that focuses on the sensitivity of interstate trade to drought and of deriving from this model the expected trade flow value between U.S. states. Next, we run a Ricardian model, whereby crop growers' profit in one state is sensitive to a local drought and to export that, in turn, depends on local drought and on drought experienced in the destination states. We complete the section by forecasting future nationwide profit with and without trade.

Gravity Model of Interstate Crop Trade

Our starting point, equation (1), is the parametrization of the gravity specification proposed by Head and Mayer (2014), which builds upon the work of Anderson and Van Wincoop (2004). Contrary to most gravity studies, we do not follow a structural approach but rather a reduced-form approach in which we approximate each term in equation (1):

$$(1)\quad X_{ijt} = \frac{Y_{it}}{\Pi_{it}} \frac{E_{jt}}{P_{jt}} \tau_{ij}$$

where X_{ijt} is the bilateral trade flow of crops from exporter i to importer j at time t. The terms Y_{it} and E_{jt} are exporter output and consumer expenditures respectively. The terms Π_{it} and P_{jt} are the multilateral resistance terms (MLRTs) for the exporter and importer respectively.

We approximate Y_{it} with exporter i's features. Ideally, these features should describe state i's potential for crop export. Thus, besides the commonly used farm industry GDP, we also include other factors affecting crop productivity, such as growing degree days (DD), precipitation (RN), and the drought conditions (DT), as follows:

$$(2)\quad Y_{it} = exp\left(\beta_1 GDP_{it}^{fm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it}\right)$$

Similarly, we approximate E_{jt} with importer j's features. Its level of demand is captured through its GDP in food manufacturing, as well as other factors affecting its own crop production, because fluctuations in the latter can affect demand for external goods. Thus, a drought in j is expected to increase j's import of crops:

$$(3)\quad E_{jt} = exp\left(\delta_1 GDP_{jt}^{fd} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt}\right)$$

Anderson and van Wincoop (2004) argue that the existence of these MLRTs is the key distinction between the structural gravity and the naïve gravity that traces back to Tinbergen (1963). We approximate these multilateral resistance terms with a GDP weighted average distance between a given state to all other states, following Wei (1996). This index proxies for the remoteness of an exporter (importer) to all potential destinations (origins). Fixed effect estimation of gravity models has become standard practice since Feenstra (2015) proposed it as an alternative to the more complex calculation of MLRTs. Yet, despite its popularity, an estimation with state-by-year fixed effects has a serious limitation in a model like ours, because they absorb any monadic effect—that is, any covariate that only varies by exporter (and is constant across all importers) or by importer (and is constant across all exporters). Our variable of interest, drought, falls in this case. To bypass this issue, we approximate the remoteness index using Wei's (1996) approach,[2] and we also incorporate two types of fixed effect structures constructed at the climate zone level[3] (each zone encompasses between two and eleven states): (*a*) climate-zone dyadic fixed effects and year fixed effects; (*b*) climate-zone dyadic fixed effects as well as importer and exporter climate-zone-by-year fixed effects.

Finally, τ_{ij} captures the dyadic effects that take place between two states. We assume the following functional form for this variable:

$$(4)\quad \tau_{ij} = exp\left(\pi_1 T_{ij} + \pi_2 C_{ij} + \pi_3 H_{ij}\right)$$

where T_{ij} is the distance between exporter and importer, measured as the travel time of trucks, C_{ij} is the contiguity dummy that takes on value 1 when states i and j share a border, and 0 otherwise. Last, H_{ij} is a dummy capturing the home-state effect (its value is 1 only when $i = j$).

Plugging equations (2)–(4) into equation (1) results in equation (5), which can be estimated by Poisson pseudo-maximum likelihood (PPML):

$$(5)\quad \begin{aligned} X_{ijt} = exp(&\beta_1 GDP_{it}^{fm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it} + \\ &\delta_1 GDP_{jt}^{fd} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt} + \\ &\pi_1 T_{ij} + \pi_2 C_{ij} + \pi_3 H_{ij} - ln(\Pi_i) - ln(P_j)) \end{aligned}$$

According to Silva and Tenreyro (2006, 2011), the PPML estimator outperforms traditional OLS when the data of bilateral trade contain many zeros and/or when the gravity model displays heteroscedastic error terms. Both phenomena are present in our sample. Indeed, the Ramsey RESET test is significant (p-value = 0.000), and the ratio of zero flow ranges from 21% (in 1997) to 25% (in 2012).

Ricardian analysis for drought impact. We start with the reduced-form Ricardian specification of Deschênes and Greenstone (2007)

[2]In order to test the validity of our choice, we regress both Wei's inward and outward MLRTs against the exporter-by-year and importer-by-year dummies (minus one time period) respectively and find a R-squared value above 0.99.

[3]Figure A1 in the appendix shows the climate regions (Karl and Koss 1984).

and provide several important modifications to it:

$$(6) \quad Y_{it} = \theta DT_{it} + \gamma \widehat{EX}_{it} + f(DD_{it}, RN_{it}) + \rho_1 PI_{it} + \rho_2 PD_{it} + \nu_i + \nu_{cz_i t} + \epsilon_{it}$$

where Y_{it} is crop producers' profit (before tax and subsidy) of growing crops in state i and year $t =$ 1997, 2002, 2007, 2012, and $\widehat{EX}_{it} \equiv \sum_{j \neq i} \widehat{X}_{ijt}$ represents the (log of) the expected export obtained from the gravity equation. This two-step approach allows us to control for the endogeneity of the trade flows (Kelejian and Piras 2014; Qu and Lee 2015) when calculating the direct and indirect (trade-based) effect of drought on profit. It is important to note that, among other characteristics such as location, timing, and duration, the spatial extent of the drought matters in this case. Geographically narrow shocks have little to no impact on prices because each state is assumed to be a price taker. Therefore, one would expect a drought of that type to decrease the volume exported and profit in the affected state, whereas other states providing the same commodity would see both exports and profits increase as a result of trade diversion. If, on the other hand, a geographically broad drought like the 2012 event in the Corn Belt takes place, it would lead to higher crop prices, which would partially offset the fall in quantity produced on profits in the exporting places. At the same time, a shortage of crops available for sale would oblige importing states to face more expensive inputs.

In equation (6), DT_{it}, DD_{it} and RN_{it} share the same meaning as in equation (5), and $f(\cdot)$ is the quadratic functional form of these variables (Mendelsohn, Nordhaus, and Shaw 1994; Deschênes and Greenstone 2007). PI_{it} is the (log of) per capita income, and PD_{it} stands for population density. These are socioeconomic controls commonly used in the Ricardian literature to capture local demand for food and how much land is used for purposes other than agriculture (Kelly, Kolstad, and Mitchell 2005). We also include the state fixed effects ν_i to capture any time-unvarying factors, such as soil quality, altitude, topography, and geographical location. Last, the climate-zone-by-year fixed effects $\nu_{cz_i t}$ —where index cz_i stands for states i in climate zone cz—are added to allow different time trends for different climate zones. Their presence is necessary because a bioenergy boom that deeply affected the net revenue of Midwestern farmers started in the second half of our study period. On the other hand, the fruit-rim states probably experienced a more moderate impact as the price indices of the fruits and vegetables have only mildly increased during the same period. For instance, corn price per bushel tripled from \$2.28 in 2006 to \$6.67 in 2012, whereas the fruit and vegetable price index increased by only 11% over the same period.

Our model specification in equation (6) is not readily comparable with that of Deschênes and Greenstone (2007) for several reasons. First, our focus is on crop production only, which is why we exclude livestock production and other activities. Our approach implies that farmers' adaptation still takes place but is limited to a switch among crops. Second, our spatial units being states instead of counties means that adaptation includes the option for production to shift its location over a larger territory. Above all, our model considers that crop growers' profit is a function of both local demand and demand from other states. This approach means that, as one state adapts to new weather conditions, it affects its demand, its trade, and hence the profit in all other states. Distinguishing clearly between the effect of weather events that take place locally and the effect of weather events in importing states allows us to highlight the spatially heterogeneous impact of these events, as each state has its unique set of trade partners. In the absence of such interregional externalities, our estimate of the marginal effect of drought on crop grower's profit would likely suffer from a missing variable bias, which would affect our results and our estimates of future crop profit (Dall'Erba and Domínguez 2016). More importantly, it could suggest misleading mitigation and/or adaptation strategies, as the role of trade would be ignored.

Data Sources and Description

Besides the trade flow data, which has been discussed in Section II, there are three additional groups of data needed to estimate our gravity specification. They are the bilateral accessibility between each pair of importer–exporter, the exporter's features, and the importer's features.

Bilateral Accessibility

This dyadic relationship is traditionally captured through distance (or travel time) and dummy variables for continuity, common language, and colonial ties in the international trade literature (Yotov et al. 2016). Here, we use a contiguity dummy and travel time only because the other characteristics do not fit the domestic trade context. The travel time is calculated by Open Source Routing Machine (OSRM) that finds the shortest path between the most populous city of each origin and destination based on existing road networks. According to Hwang et al. (2016), the shipments of agricultural commodities are almost all moved by truck; therefore, travel time based on the highway system is a more relevant proxy for trade costs than the geographic distance widely used in international trade studies.

Exporter's Features

This set of monadic variables describes the supply capacity of a potential exporter. We select the gross domestic product in the farming industry (NAICS code No. 11), as it captures the size of the current production in the origin state. It comes from the U.S. Bureau of Economic Analysis (2020). Besides the current production, the crop stock left from the previous year could be an additional source for supply capacity. This piece of information, collected from USDA's National Agricultural Statistics Service (NASS), is used as an additional exporter feature in one of the robustness checks. Finally, as indicated in section III, a set of weather characteristics, including the variable of interest, also belongs to this category. However, because these variables are also used to capture the importer's features and for the Ricardian analysis, we postpone their description until the latter part of this section.

Importer's Features

We choose the GDP in food manufacturing (NAICS code No. 311) from Bureau of Economic Analysis (BEA) as a proxy for a state's capacity to purchase crop products from any origin state. Because the food manufacturing industry buys 38.3% of the crops (BEA, 2014), whereas the direct demand by final consumers is only 29.1% of the production, we believe it is a better than including the overall per capita GDP. However, as part of our robustness checks, we also collect the data of total population from the U.S. Census Bureau (USCB) and the bioenergy capacity from USDA's Economic Research Services (2.4% of the direct purchases of crops). They are used as proxies for final demand and demand for energy use, respectively.

The weather conditions affect crop productivity of both the exporters and the importers. These conditions are captured through three variables: growing degree days (GDD), total precipitation, and drought. GDD, a measure of heat accumulation used by agronomists, is calculated based on daily average temperature, with 8°C as the lower bound and 32°C as the upper bound (Schlenker, Michael Hanemann, and Fisher 2006). Meanwhile, we sum daily precipitations throughout the growing season (April 1 to September 30, according to Deschênes and Greenstone 2007) to obtain the total precipitation. The raw raster data of daily average temperature and precipitation is from the North American Regional Reanalysis (NARR) dataset (Mesinger et al. 2006). ArcGIS 10.2 is used to convert raster data to the county level. After calculating the county-level GDD and total precipitation data, we aggregate them to the state level with a weight proportional to each county's cropland acreage.

The starting point of our drought index calculation is the raster surface of monthly Palmer Drought Severity Index (PDSI) from the National Oceanic and Atmospheric Administration (NOAA). We first calculate the zonal statistics on the U.S. county layer and then transform the county-level monthly PDSI records into a weighted count of severe drought days at the state level as follows:

$$\text{(7)}\quad \text{Severe drought days}_s = \sum\nolimits_{c \text{ in state } s} \left\{ \underbrace{\left[\sum\nolimits_{m=1}^{12} \mathbf{1}(\text{PDSI}_{c,m} < -3)\right]}_{\text{count drought months}} \underbrace{\times 30}_{\substack{\text{convert}\\ \text{months}\\ \text{to days}}} \right\} \times \underbrace{\frac{\text{cropland}_c}{\text{total cropland}_s}}_{\substack{\text{weight by}\\ \text{county } c\text{'s}\\ \text{cropland acreage}}}$$

The calculation involves two steps: first, we transform the number of severe drought months (i.e., with a PDSI < −3) for each county into a number of days to capture the duration of droughts. Next, we weight that sum by the share of each county's cropland acreage to reflect the extensiveness of droughts. We choose −3 as the cut-off to identify severe droughts as recommended by the U.S. Drought Monitor.

Besides the weather data, which have been discussed above, there are two additional groups of data needed to estimate the Ricardian equation (equation 7). They are the socioeconomic controls (population density comes from the Census, and per-capita income comes from BEA) and crop profit, the dependent variable. The latter corresponds to the difference between the value of sales by crop farm (before tax and subsidy) and the corresponding production costs. The raw sales and costs data are from the Agricultural Censuses. The Census only reports cost by expense type instead of by commodity, which leads us to estimate the production cost of crop farms. In order to do so, we first classify the different types of cost into three categories: crop related, livestock related, and universal (or fixed cost). Then we add all the crop-related expenses to the universal expenses weighted by the value of sales by crop farms to all farms. Table 1 offers a summary of all the data used in this paper.

Results, Robustness Checks, and Projections

This section starts with a report and discussion of the estimates from our gravity specification along with several robustness checks and a breakdown of the intensive and extensive margins of trade due to drought (subsection A). Next, we display the results of our Ricardian model and assess the impact of future weather conditions, including expected drought events, on crop growers' profits with and without trade (subsection B).

Gravity Equation Estimation

Table 2 reports the OLS and PPML regression results of equation (5) with the two fixed effect structures mentioned previously. The presence of zero flows causes the OLS estimator to drop around one third of the observations,

Table 1. Data and Sources Description

Notation	Description	Sources	Usage
X_{ij}	Interstate trade flows of crops	FAF[4]	Gravity equation (dep. Var.)
T_{ij}	Travel time between the most populous cities	Shapefile	Gravity equation
C_{ij}	Common border dummy	Shapefile	Gravity equation
H_{ij}	Intra-state trade dummy	Shapefile	Gravity equation
GDP^{fm}	Farm industry GDP in the origin	BEA	Gravity equation
GDP^{fd}	Food manufacturing GDP in the destination	BEA	Gravity equation
DD	Growing degree days in both origin and destination	NARR	Gravity equation and Ricardian analysis
RN	Total precipitation in both origin and destination	NARR	Gravity equation and Ricardian analysis
DT	Severe drought days in both origin and destination	NARR	Gravity equation and Ricardian analysis
y	Profit per acre for crop production farms	USDA NASS	Ricardian analysis (dep. Var.)
PD	Population density	Census Bureau	Ricardian analysis
PI	Per capita income	BEA	Ricardian analysis
N/A	Bioenergy capacity in the destination	USDA ERS	Robustness checks
N/A	Total population in the destination	Census Bureau	Robustness checks
N/A	Crop stock in the end of previous year	USDA NASS	Robustness checks

Note: Notation, description, data source and usage of the variables used in equations (6) and (7).

as the dependent variable is in log terms. On the other hand, the PPML estimator requires no transformation of equation (5). As expected, each estimator generates different results; however, the difference is particularly acute for the bilateral trade cost proxies. Although there are only minor differences in the PPML coefficient estimates reported in columns 3 and 4, the latter specification is our preferred one because it includes climate-zone-by-year fixed effects, whose presence is consistent with empirical evidence and trade theory (Yotov et al. 2016).

The results of column (4) confirm that severe drought days in the origin state have a negative impact on export because they reduce the state's supply capacity. However, this effect is not statistically significant, even at 10%. More drought days in the destination state, on the other hand, significantly increase that state's demand for imports. This difference could be explained by both pulling and pushing factors: on the supply side, farms in the origin state can rely on inventories built over the previous years to compensate for the current year's limited production (Westcott and Jewison 2013). On the demand side, however, the food processing industry in the destination states enjoys much less flexibility. Indeed, in the event of a local drought, a state becomes more dependent on imports because food manufacturing plants require the usual level of crop inputs, and their location is fixed in the short term. A robustness check, described further below, will indicate that it is true for livestock production too.

We also note that, among the remaining weather variables, a statistically significant relationship exists between precipitation in the destination state and exports. The rest of the covariates are significant, and their signs meet our expectations. For instance, the contiguity dummy has a significant and positive impact on bilateral trade. The travel time, on the other hand, plays a significant negative role. The exporting state's farm industry GDP, as the proxy for the origin's supply capacity, has a positive effect. The food manufacturing GDP, as the proxy for the destination's purchasing power, affects trade flows positively as well. The remoteness indices for both exporter and importer are positive, as trade theory suggests (Anderson and van Wincoop 2004).

To tease out the validity of our results, we present in table 3 a list of robustness checks,[4] all of which are based on specification (4) in table 2. The first two robustness checks are based on specifying new fixed effects. The first type we add to our benchmark specification is fixed effects by USDA's farm production regions. Besides the climate normal, USDA takes also into account other factors, such as agricultural activities, soil qualities, and topography, when grouping the states into farm production regions. The second, alternative fixed effects we try are one-sided, exporter-by-year fixed effects. The latter absorbs any origin-specific factors, so only the sensitivity of export to a drought in the destination states can be measured by this approach. As a result, we also run a complementary model with one-sided, importer-by-year fixed effects (table A1).

The next two robustness checks consist of testing the results when the two types of trade flows, cereal grain (SCTG 02) and other main crops (SCTG 03), are treated individually. Indeed, one would expect that their individual sensitivities to drought differ, because the fields growing cereal grains are more likely to be rain fed than those growing fruits and vegetables. Furthermore, because the monetary value of the shipments is used as the dependent variable in the default gravity analysis, identification may be challenged by the fact that severe droughts usually trigger a price increase for the major crops. To avoid this confounding effect, we test the robustness of our results by comparing them to the use of the actual physical quantities of the interstate shipments (table A2).

Another potential identification problem comes from severe drought days that are measured for the entire year. Lobell et al. (2014) suggest that if a drought occurs during the latter stage of the growing season, it might cause larger damage to crop yield. In order to examine the impact of drought timing on our results, we define two alternative measures of severe drought days. The first one counts drought only during the growing season (April to September), whereas the other one counts only the drought that occurred in the last three months of the growing season (July, August, and September).[5] Finally, we examine the sensitivity of our results to the addition of other explanatory variables that capture the pull and push factors of the flows.

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[4]The complete results of these robustness checks are presented in Tables A1–A3 in the appendix.

[5]Note that, in addition to questions about the period of the event, other drought indices such as the Standardized Precipitation Index (SPI) or the Standardized Precipitation Evapotranspiration Index (SPEI) would raise a significant amount of uncertainty associated to the "correct" time scale needed for their calculation (McKee et al. 1993). Therefore, we disregard their use in this paper.

Table 2. Estimation Results for the Gravity Equation (()

	OLS		PPML	
	(1)	(2)	(3)	(4)
Common border	1.611**	1.617**	1.015**	1.006**
	(0.15)	(0.15)	(0.23)	(0.23)
Travel time	–1.920**	–1.911**	–0.607**	–0.631**
	(0.13)	(0.13)	(0.12)	(0.12)
Drought days (orig.)	–0.044+	–0.061+	–0.03	–0.029
	(0.03)	(0.03)	(0.03)	(0.03)
Drought days (dest.)	0.055*	0.002	0.069**	0.089*
	(0.03)	(0.03)	(0.03)	(0.04)
GDP (orig.)	1.358**	1.366**	0.772**	0.781**
	(0.05)	(0.05)	(0.09)	(0.10)
GDP (dest.)	1.026**	1.024**	0.456**	0.458**
	(0.04)	(0.04)	(0.05)	(0.05)
Remoteness index (orig.)	2.650**	2.694**	1.152*	1.189**
	(0.41)	(0.42)	(0.46)	(0.46)
Remoteness index (dest.)	3.208**	3.291**	0.446	0.63
	(0.42)	(0.45)	(0.64)	(0.73)
Degree days (orig.)	–0.021	0.019	0.15	0.117
	(0.27)	(0.28)	(0.35)	(0.37)
Degree days (dest.)	0.874**	1.021**	0.535	0.597
	(0.26)	(0.27)	(0.36)	(0.38)
Precipitation (orig.)	–0.347*	0.008	–0.148	–0.144
	(0.15)	(0.20)	(0.17)	(0.26)
Precipitation (dest.)	0.199	0.419*	0.505**	0.723**
	(0.15)	(0.21)	(0.19)	(0.26)
Home by year FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Climate zone dyadic FE	Yes	Yes	Yes	Yes
Climate zone by year FE (exporter and importer)	No	Yes	No	Yes
Num. of obs.	6,401	6,401	9,216	9,216
Adj. R squared	0.551	0.568		
Pseudo R-squared			0.827	0.834

Note: The dependent variable is interstate trade flows of crops. Standard errors in parentheses.
$^{+}p < .10$,
$^{*}p < .05$,
$^{**}p < .01$.

Table 3. Alternative Specifications of the Gravity Equation

	Drought days in the origin state		Drought days in the destination state	
	Estimates	Standard error	Estimates	Standard error
Benchmark (from column 4 of table 2)	–0.03	(0.03)	0.09*	(0.04)
Robustness checks:				
(1) use USDA farm production region	0.03	(0.25)	0.07*	(0.02)
(2) use one side exporter/importer-by-year FEs	–0.03	(0.03)	0.09**	(0.03)
(3) trade flows for cereal grain only (SCTG02)	–0.03	(0.04)	0.12**	(0.05)
(4) trade flows for other crops only (SCTG03)	–0.03	(0.03)	0.07*	(0.05)
(5) trade flows in volume measure (SCTG02)	–0.04	(0.05)	0.10*	(0.05)
(6) trade flows in volume measure (SCTG03)	–0.03	(0.03)	0.09*	(0.04)
(7) drought during growing season	–0.04	(0.04)	0.09*	(0.04)
(8) drought during last 3 months before harvest	–0.00	(0.04)	0.09*	(0.05)
(9) add total population and crop stock	–0.03	(0.04)	0.09*	(0.05)
(10) add ethanol and biodiesel capacity	–0.04	(0.05)	0.13**	(0.05)

Note: The dependent variable is interstate trade flows of crops. Details of the estimates appear in tables A1–A3.
$+ p < 0.10$,
$* p < .05$,
$** p < .01$

Specifically, the crop stock left from the previous year can be considered as a potential contributor to the supply capacity of the origin state. In addition, the ethanol and biodiesel producers have quickly established themselves as major buyers of corn and soybean due to the bioenergy boom of the recent years, and hence, their role needs to be investigated too (table A3).

All the robustness checks confirm the results displayed in table 2: drought in the origin state has a negative but non-significant effect on export, whereas a drought occurring in the destination states would significantly stimulate a state's export of crops.

In addition, we explore further how drought affects the extensive and intensive margins of the crop trade flows through the decomposition suggested by Felbermayr and Kohler (2006) and illustrated graphically in Mayer and Gianmarco (2007). In figure 4, we pay close attention to two types of drought: those occurring anytime throughout the year (Panel (a)) and those occurring in the three-month window before harvest (Panel (b)). Each panel in figure 4 shows the extensive margin (i.e., number of trade partners), intensive margin in monetary terms (millions of dollars per partners), and intensive margin in physical terms (tons per partner). The point estimates of the drought variable and their associated 95% confidence interval are represented in each panel for four different types of trade flows (inward flows and outward flows for each SCTG group). Three important results emerge from this analysis. First, a drought reduces the extensive margin of the export flows. Indeed, states experiencing a severe drought reduce the number of states to which they export grains (SCTG2). Second, we find that a drought in the origin state reduces the intensive margin of grain export, whether the latter is measured in value or volume. We also note that the magnitude of the intensive margin effect is nearly twice as large as the value of the extensive margin effect. Third, the average effect of a drought in the destination state on the intensive margin of grain export is positive and large at 0.1. In sum, this decomposition allows us to highlight that droughts affect the exported volume/value more than the number of destinations. We also note that these effects are asymmetric across commodities, as the average extensive and intensive margins for trade in vegetable, fruit, and oil seeds (SCTG 03) are close to zero. The details of all these results appear in appendix tables A4–A6.

Ricardian Model with Trade and Future Projections

The results of our Ricardian model with trade (equation 6) are reported in table 4 (columns 3–4) and compared with estimates that would ignore trade (columns 1–2). It follows from equation (6) that, unlike the case of the Ricardian model without interstate trade, the derivative of Y_i with respect to drought does not only equal θ but also takes a value determined by the *i* or *j* element of the partial derivative matrix S below:

$$\mathbf{S} \equiv \frac{\partial \mathbf{Y}}{\partial \mathbf{DT}} = \begin{bmatrix} \frac{\partial Y_i}{\partial DT_i} & \cdots & \frac{\partial Y_i}{\partial DT_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial Y_n}{\partial DT_i} & \cdots & \frac{\partial Y_n}{\partial DT_n} \end{bmatrix}.$$

Based on the terminology introduced by LeSage and Kelley Pace (2010) for spatial interaction models, we define the average direct impact of a drought on profit as the average of S_{ii} or $\frac{1}{n}\sum_{i=1}^{n}\frac{\partial Y_i}{\partial DT_i} = \frac{1}{n}\mathrm{tr}(\mathbf{S})$. Furthermore, whereas typical regression coefficients are interpreted as the average effect of the explanatory variable on the dependent variable over the sample of observations, our approach ensures that each of these diagonal derivatives is composed of the following elements:

$$(8) \qquad \frac{\partial Y_i}{\partial DT_i} = \theta + \frac{\partial EX_i}{\partial DT_i} = \theta + \gamma \times \sum\nolimits_j \frac{\partial X_{ij}}{\partial DT_i} = \theta + \gamma \times \beta_4 \times \frac{EX_i}{DT_i}$$

Equation (8) indicates that the first, direct channel of transmission for a change in drought in *i* on profit in *i* comes from the partial differentiation of equation (6) with respect to severe drought days (DT). The second channel emanates from the impact that a change in drought in *i* will have on exports from *i*. The latter marginal effect derives from the definition of the variable EX and from using $\beta_4 = \frac{\partial \log(X_{ij})}{\partial \log(DT_i)}$ from equation (5).

In addition, the sum of the off-diagonal element of row *i* in matrix S corresponds to the export-weighted spillovers of drought in

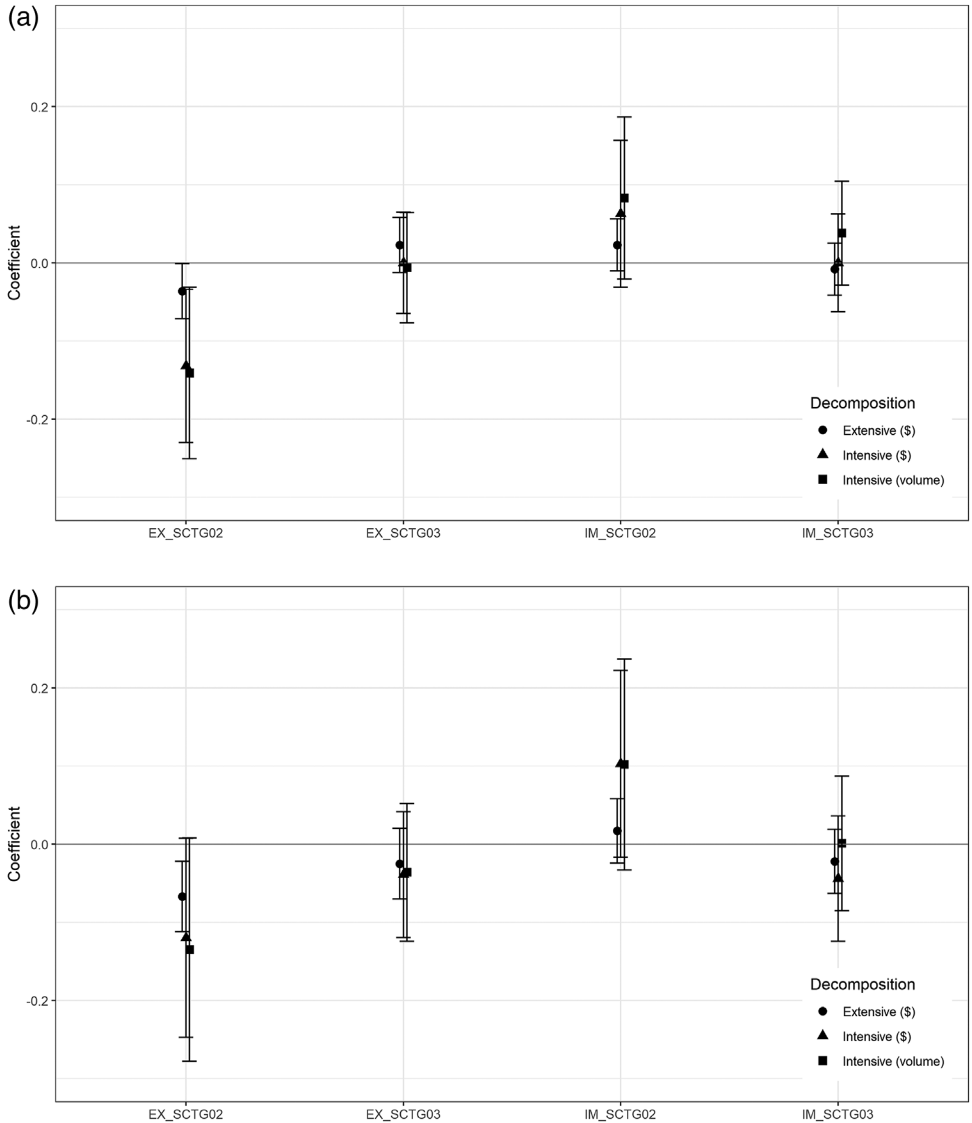

Figure 4. Results for the extensive and intensive trade margins

Note: The figure shows the point estimates (within the 95% confidence interval) of the severe drought impact on extensive margins and intensive margins in monetary terms and intensive margins in volume of production. Panel (a) focuses on number of days with a drought during the full year. Panel (b) focuses on number of days with a drought three months before the growing season. Details of the calculations are reported in tables A4–A6.

locations *j* on the agricultural profit of location *i* (inward effect). It represents the total impact on Y_i from a drought occurring in any other state:

$$(9)\qquad \sum_{j\neq i}^{n}\frac{\partial Y_i}{\partial DT_j}=\sum_{j\neq i}^{n}\gamma\times\frac{\partial X_{ij}}{\partial DT_j}=\sum_{j\neq i}^{n}\gamma\times\delta_4\times\frac{X_{ij}}{DT_j}$$

Similarly, the sum of the off-diagonal elements of column *i* in matrix S allows us to calculate how a drought in state *i* affects its export and modifies the profit of the crop growers in locations *j* (outward effect) as follows:

$$(10)\qquad \sum_{j\neq i}^{n}\frac{\partial Y_j}{\partial DT_i}=\sum_{j\neq i}^{n}\gamma\times\frac{\partial X_{ij}}{\partial DT_i}=\sum_{j\neq i}^{n}\gamma\times\delta_4\times\frac{X_{ij}}{DT_i}$$

Figure 5 displays the direct effect, whereas figure 6 displays the inward spillover effect (panel a) and the outward spillover (panel b) of one extra week of severe drought on the

Table 4. Ricardian Estimation Results

	(1) No trade	(2) No trade	(3) Trade	(4) Trade
Drought	0.091	0.235	0.198	0.38
	(0.15)	(0.17)	(0.14)	(0.17)
GDD	−0.062	−0.096	−0.186	0.135
	(0.17)	(0.29)	(0.16)	(0.27)
GDD squared	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Precipitation	4.461	26.764^{+}	4.905	25.098^{+}
	(9.04)	(14.10)	(8.46)	(13.14)
Precipitation squared	−0.174	−0.619	−0.131	−0.612^{+}
	(0.28)	(0.38)	(0.27)	(0.35)
Per capita income	10.179	18.935	9.241	9.991
	(12.83)	(16.48)	(12.01)	(15.51)
Per capita income squared	−0.123	−0.207	−0.141	−0.165
	(0.13)	(0.16)	(0.12)	(0.15)
Density	3.461*	4.216*	3.326*	3.392*
	(1.50)	(1.77)	(1.41)	(1.66)
Density squared	−0.001	0.000	0.000	0.000
	(−.001)	(0.00)	(0.00)	(0.00)
Total exports			0.038**	0.045**
			(0.008)	(0.011)
Constant	−298.014	−858.921	−147.364	−776.66
	(450.80)	(718.06)	(423.31)	(669.57)
Year FE	Yes	No	Yes	No
Climate zone by year FE	No	Yes	No	Yes
Observations	192	192	192	192
R-squared	0.50	0.63	0.57	0.68

Note: The dependent variable is crop growers' profit. Standard errors in parentheses.
$^{+}p < .10$,
$^{*}p < .05$,
$^{**}p < .01$.

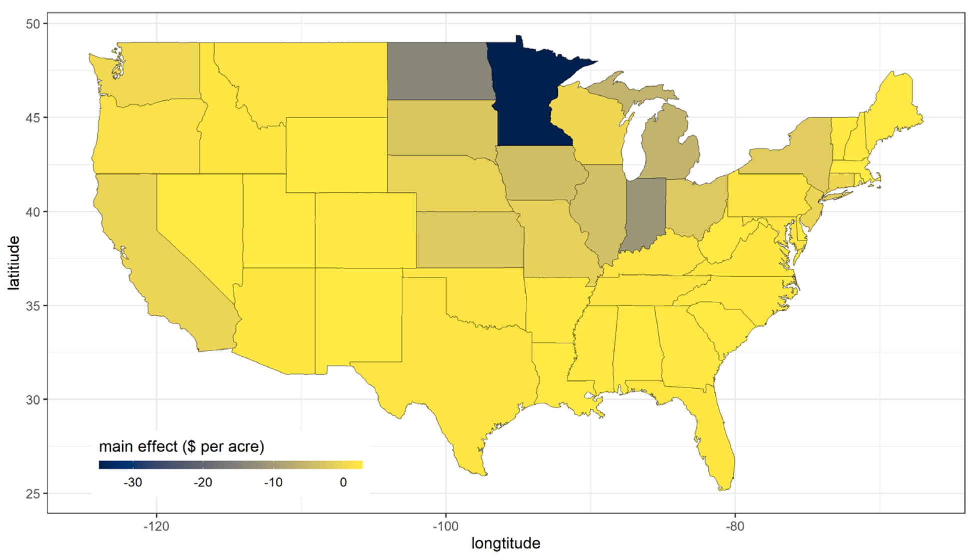

Figure 5. Spatial distribution of the direct effect of drought events on farm profits

Note: The figure shows the direct effect of one extra week (seven days) of severe drought on the per-acre agricultural profit of each state.

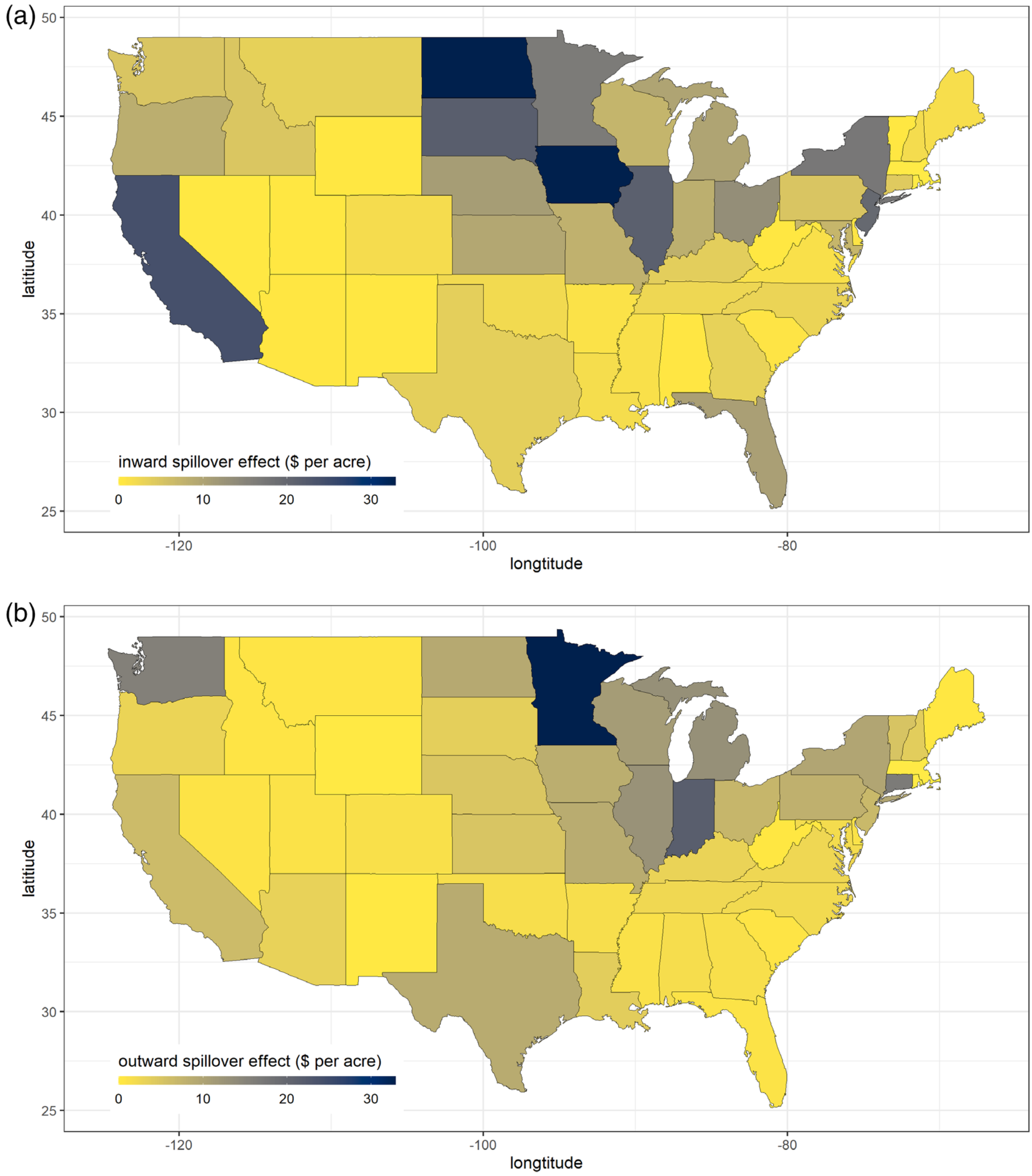

Figure 6. Spatial distribution of the spillover effect of drought events on farm profits

Note: The figure shows the spillover effect of one extra week (seven days) of severe drought on the per-acre agricultural profit of each state. Panel (a) displays the inward spillover effects and illustrates the effect of one additional week of drought in all states importing from each state. Panel (b) displays the outward spillover effects and illustrates the effect of one additional week of drought in the crop growers' profit in the importing state.

per-acre agricultural profit of each state.[6] As expected, figure 5 suggests the direct effect of a severe drought on profit is negative. Further investigation reveals that it is the trade channel that drives the results. This finding helps explain why California and the Midwest, where the main crop exporters are located, experience a greater loss than the rest of the country after one additional week of droughts.

Panel (a) in figure 6 displays the inward spillover effects, whereby the results display the impact on origin state *i* of one additional week of drought occurring in all the states *j* importing from *i*. It can be seen that the Corn Belt states, such as Iowa, Illinois, and North Dakota, and the other "key" players such as

[6]For each state, the value and standard error of the effects reported in figures 5 and 6 are shown in Tables A7 and A8 respectively.

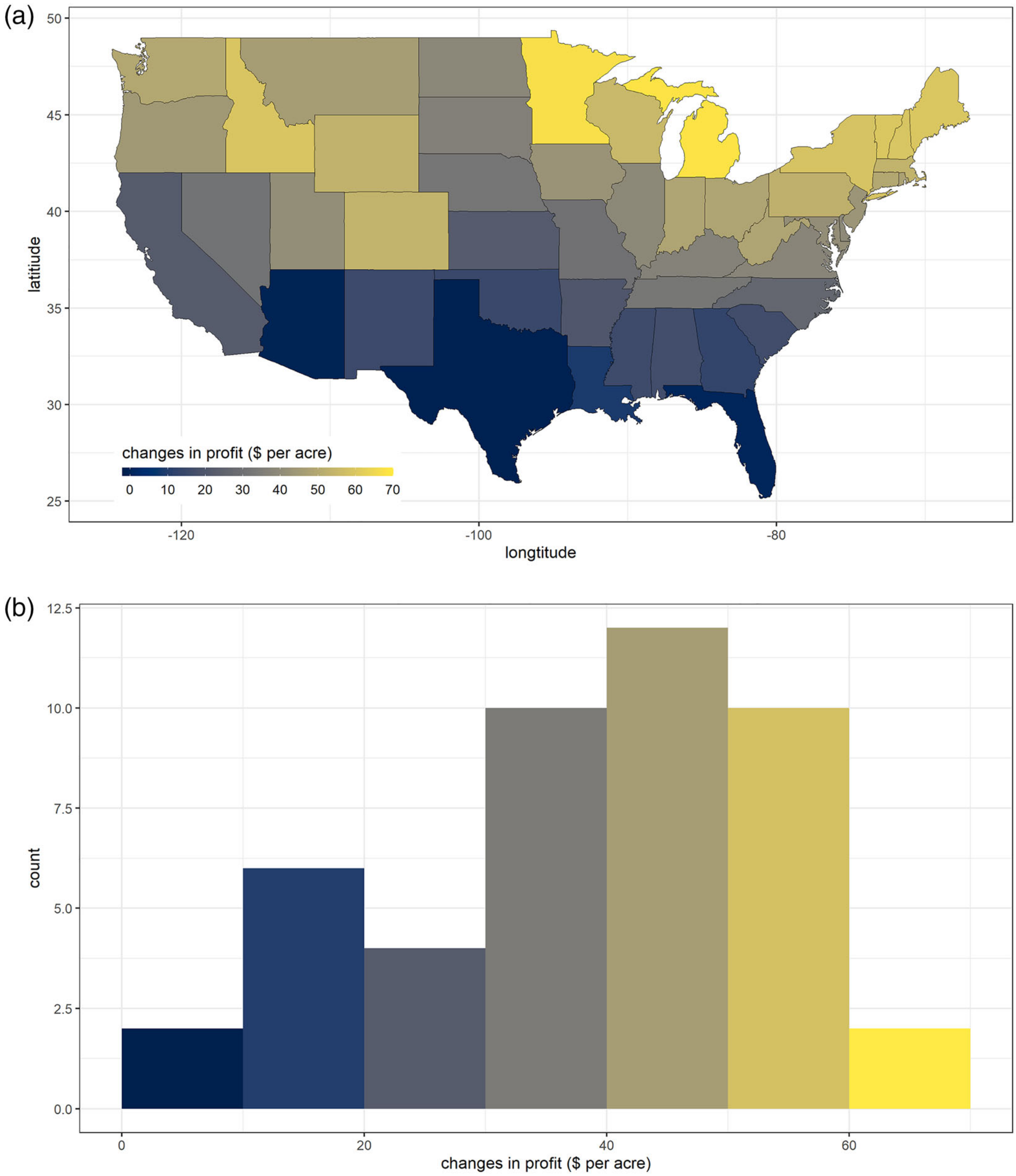

Figure 7. The average mitigation effect of trade.

Note: The figure shows the mitigation effect of trade over four different climate mode. Panel (a) shows the spatial distribution. Panel (b) shows the density distribution.

California would benefit the most from distress in the states to which they export. Finally, Panel (b) illustrates the spatial distribution of the outward spillover effects of state *i*. They correspond to the average changes in the crop growers' profits in *j* arising from one extra week of drought in the origin state *i*. Our results show that the trade partners of Minnesota, Indiana, and Washington benefit the most from a drought in the latter states. We also note that, on average, the Corn Belt states display larger outward spillover effects than the rest of the sample. As for the inward spillovers, this result comes from their key position in the interstate trade system.

Last, we estimate the impact of future weather conditions on the crop growers' future profit when trade is accounted for and ignored. Interstate trade should be seen as an efficient adaptation mechanism if the nationwide predicted profit with trade is significantly greater than the one without trade. In the benchmark scenario, we use the marginal effect of the weather variables on profit calculated from the model without trade (table 4, column 2). In the alternative scenario, the trade-induced spillovers emanating from equation (6) are also accounted for (table 4, column 4). In order to keep our results in tune with the current literature, we follow the usual approach of holding all the non-weather-related variables constant in both equations (5) and (6). It allows us to calculate the change in profit due exclusively to the expected change in weather conditions.

Following the suggestion of Burke and Emerick (2016), we use four different future climate models in order to check the robustness of the results against climate uncertainty. These models are the CRCM-CCSM, the CRCM-CGCM, the MM5I-CCSM, and the RCM3-GFDL.[7] All four models are a combination of one regional climate model focusing on North America (represented by the first four characters before the hyphen) and one general circulation model (represented by the last four characters). The base period for these models is 1968–2000, and their projections are for 2038–2070. We use the difference between past and future averages of temperature and precipitation that these models generate to do our simulations. For changes in severe drought days, we adopt the self-calibrated PDSI data of Dai and Zhao (2017), which, in spite of its recent publication, have been used in several contributions to quantify the future drought patterns due to climate change (see Zhao and Dai 2017; Huang et al. 2017; Trenberth, Zhang, and Gehne 2017, to name a few). This dataset contains global monthly PDSI records from 1900 to 2100 at a 2.5-degree spatial resolution. Future PDSI data are projected based on fourteen different general circulation models (GCMs). We use the average of all fourteen GCMs, calculate the average severe drought days for the base (1968–2000) and the future (2038–2070) periods using equation (7), and then take their difference. The average change is 1.8 more days of drought (std.dev. = 2.0) with the maximum change experienced in Utah (8.2 more days) and the minimum in Florida, Maine, Maryland, New Hampshire, Pennsylvania, and West Virginia, as they do not expect any increase in severe drought days.

The difference between the results of our simulation experiments with and without trade (table 4, columns 4 and 2, respectively) are reported in figure 7. The map in panel (a) displays for each state the magnitude of the expected capacity for the interstate trade to mitigate the adverse effect of climate change on crop profit.[8] As expected, the magnitude of the mitigation is greater for the main crop producers and exporters of the Midwest. Among them, Michigan and Minnesota are the two biggest beneficiaries. We calculate that, at the national level, interstate trade has a mitigation effect worth \$ 14.5 billion, as its presence transforms an expected loss of \$ 11.2 billion without trade into a \$ 3.3 billion profit compared to the average historical value. Furthermore, Panel (b) displays the histogram of the average mitigation effect. It shows that thirty three states should expect a mitigation effect due to trade worth at least \$30 per acre. It represents as much as 15% of the average national farm profit measured over 1997–2012. Details about the projected change in profit with and without trade are available for each state in appendix table A9.

Conclusion

There is increasing interest in the capacity for trade of agricultural commodities to act as a successful mitigation mechanism for climate change. Although the evidence at the international level seems promising, this manuscript is the first one to deal with domestic trade in which the capacity of adaptation is limited by the range of nationally produced crops, country-wide weather conditions, and the national transportation network. The focus is on the U.S. because the domestic market (91.2% of the nation's intermediate and final demands for agricultural products are satisfied by domestic production) and China's retaliatory tariff increase on various U.S. agricultural goods in 2019–2020 oblige

[7] CRCM stands for Canadian Regional Climate Model v4. MMI5 stands for Penn. State University NCAR Mesoscale Model. RCM3 stands for International Centre for Theoretical Physics Reg. Climate. CCSM stands for Community Climate System Model. CGCM stands for Coupled Global Climate Model. GFDL stands for Geophysical Fluid Dynamics Laboratory GCM.

[8] Because the results are similar among the four regional-global climate models, we only display the map associated with the average results. However, the map for each model is available upon request.

us to prioritize the domestic rather than the international trade to evaluate the future of the nation's food security. In addition, a domestic approach allows us to ignore the confounding effect of traditional international trade barriers, such as tariffs, and to contribute to a growing body of econometric literature on the impact of future weather conditions on U.S. agriculture. A large majority of this literature has focused exclusively on local weather impact; hence, it has overestimated the nationwide impact of crippling events like drought, it has completely disregarded the role of trade-induced spillovers, and it has failed to generate impact estimates that are spatially heterogeneous, even though it is well-known that each state has its unique set of trade linkages.

Our results indicate that crop grower's profit is sensitive to local weather conditions and is positively affected by exports. The latter, in turn, significantly increase when destination places experience a drought, a result confirmed in all the robustness checks we performed on our gravity estimates. Because a sudden drought in destination places reduces their crop production but not the demand from their livestock and food manufacturing sectors, imports increase. Inversely, a drought reduces the capacity for a state to export, and further investigations through a decomposition of the intensive and extensive trade margins allow us to highlight that droughts decrease the exported volume and value more than the number of destinations places to which a state exports.

We also estimate the capacity for trade to mitigate the adverse effect of future weather conditions and discover that it is worth \$ 14.5 billion (in 2012 prices). Indeed, a \$ 11.2 billion nationwide loss in crop growers' profits is expected when trade is disregarded, as this traditional approach exacerbates the local impact of future local weather conditions. However, when trade is accounted for, its presence turns our projections into a \$3.3 billion gain, or a 3.4% percent increase in annual profit. As a result, our approach provides new insights into the expected impact of future weather conditions in a Ricardian framework, as, for the first time in the literature, it extends the set of possible mitigation/adaptation strategies to account for policies increasing domestic trade linkages.

Future research could take our approach in several directions. First, one could consider the trade flows of all agricultural activities to come closer to the traditional Ricardian measurements, where all agricultural sectors are bundled up. This approach could then consider higher order effects, such as when the sale of crops used for animal feed affects, in turn, the interstate trade of live animals to the food manufacturing industry. We anticipate that this approach would find an even larger capacity for the domestic trade to mitigate the effect of future weather conditions on agricultural profit. Second, we acknowledge that the Ricardian literature lacks a structural framework from where all these mechanisms can be derived. Future research should consider combining the general equilibrium model this manuscript builds upon with the Ricardian approach framework. Third, our results provide some useful insights into the food transport industry. For instance, the Mississippi River watershed is a major shipping route for the grains grown in the Midwest. As a result, a drought in this area would have negative consequences on the barge traffic and all the jobs associated with it (Ziska et al., 2016). At the same time, new transportation links could be developed based on expected future weather conditions and associated future crop production locations. Finally, other extreme weather events such as floods and early frost could be considered, as their frequency and intensity are expected to increase in the future (IPCC, 2014), and their damaging effects on agriculture have been highlighted in the literature (e.g. Zhang et al. 2013; Kukal and Irmak 2018).

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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