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ABSTRACT: According to the current IPCC report, climate change will increase the probability of occurrence of droughts. 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, including droughts, 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 a large number of climate impact studies focus on its agriculture and around 90% of the U.S. agricultural 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, the general equilibrium agricultural profit depends on both local and trade partners' weather conditions, including drought. Projections based on future weather data challenge the estimates of the current climate impact literature by revealing that trade is expected to act as a $ 14.5 billion adaptation tool as it converts the expected profit losses without trade into expected profit gains.

KEY WORDS: Drought Impact Evaluation, Intra-national Trade, Agricultural Profit.

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I. Introduction

Recent decades have witnessed changes in weather conditions, including an increase in the frequency and intensity of extreme weather events, and the most recent report of the Intergovernmental Panel on Climate Change predicts that this trend should continue in the near future (IPCC, 2014). 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 et al., 1994; Deschênes and Greenstone, 2007, for the U.S.; Lippert et al., 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 adaptation mechanism to climate change (Reilly and Hohmann, 1993; Rosenzweig and Parry, 1994; Julia and Duchin, 2007; Schenker, 2013). Trade theory (Krugman, 1979; 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 places based on the current level of complementarity (e.g. crops used for animal feeding) or of substitution with local production. However, in the long run new climate conditions will have the potential to disrupt current competitive advantages, hence leading 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 higher yield volatility as well. Reimer and Li (2009) and Ferguson and Gars (2017) indicate that short-run production losses following a sudden drought or a flood can be substituted for imports (trade creation). Moreover, 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).

Yet, it is important to note that the capacity of international trade to cope with expected climate changes has been challenged in a recent contribution by Costinot et al. (2016). Based on a vast new dataset containing agricultural productivity for million fields around the world, their results show that international trade plays only a minor role in climate mitigation compared to domestic production reallocation. Therefore, they expect that new climate conditions will force countries to decide whether crops whose yield has fallen need to be relocated within the country or simply imported instead. However, their estimates disregard the role 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) and who are primarily self-sufficient. For instance, 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). As a result, it is likely that new climate conditions will bring about larger changes to its domestic rather than international trade. Finally, the current White House administration's tendency to reconsider established trade agreements, including those dealing with agricultural commodities and livestock[1], obliges us to investigate the domestic trade further as the nation's future food security may increasingly rely on it.

As such, the first objective of this paper is to assess the degree of sensitivity of domestic agricultural trade flows to new weather conditions, including drought, the extreme weather event commonly seen as the largest threat to agriculture and global food security (Wilhite, 2000). All previous contributions at the international level emphasize climate change as changes in long-run temperature or precipitation but they miss the role of drought events as well as their future frequency and intensity. The domestic impact of droughts and their spatial externalities has been studied through structural modelling approaches such as input-output (y Pérez and Barreiro-Hurlé, 2009), computable general equilibrium (Horridge et al., 2005) and price-endogenous regional programing (Salami et al., 2009) but, as far as we know, never in a structural gravity model (e.g. Anderson and van Wincoop, 2003; Arkolakis et al. 2012; Head and Mayer,

[1] For instance, China imposed a 25 percent retaliatory tariffs on American soybeans on July 6, 2018. It led the price of the commodity to fall about 17 percent on the decline in the soybean futures market.

2014). In addition, the gravity framework has been frequently applied to agricultural trade (see, among others, Cho et al., 2002; Sarker and Jayasinghe, 2007; Grant and Lambert, 2008; Sun and Reed, 2010; Jean and Bureau, 2016) but with a sizable focus on international flows due to a great interest for the impact of trade agreements. 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 manmade trade barriers, market structure differences and domestic agricultural subsidies.

This manuscript fills a gap in the literature by offering the first application of the gravity model to the agricultural trade flows measured across the U.S. states. Based on newly-released Freight Analysis Framework with detailed drought data measured at a fine spatial and temporal resolution, the results of our structural gravity model show that drought in the destination state significantly increases the bilateral trade flows of crops. Moreover, when droughts occur in the origin state, they reduce its export capacity to other states, but the effect is not as large as the trade creation that results from droughts in the destination state.

The second objective of this manuscript consists in measuring how the farmers' profits change as a result of new weather conditions and of new domestic trade patterns. This second question calls upon the so-called Ricardian model of climate change (Mendelson et al., 1994; Schlenker et al., 2006; Deschênes and Greenstone, 2007), a reduced-form regression model where the dependent variable, land value or agricultural profit, presents the advantage of accounting for any agricultural activity and for substitution as a way of adapting to new climate conditions. Here, we rely on the panel data approach of Deschênes and Greenstone (2007) where agricultural profit is regressed on year-to-year weather fluctuations and a set of fixed-effects that account for additional unobservables. We extend it to include interstate dependence through trade. In itself this omitted variable does not correct for the other omitted variable biases their approach has been criticized for, namely the omitted weather variables (Zhang et al., 2017) and the omitted effect of storage (Fisher et al., 2012), but the latter two will also be dealt with in our long list of robustness checks.

Our general equilibrium results show that exports act positively and significantly on the profit derived from crops production, which indicates that droughts in partner states contribute positively to the (pre-subsidy) agricultural profit in the origin states. Our results are not readily comparable with those of Deschênes and Greenstone (2007) where all agricultural activities, including livestock, are bundled together in the calculation of agricultural profit. Hence, our approach implies that farmers' adaptation still takes place but it does not include a possible switch to livestock. On the other hand, our spatial units being states instead of counties means that adaptation includes the option of production to shift its location over a larger territory. Finally, another element that differentiates our estimates from the current literature is that we consider both local demand, as captured through the usual per capita income proxy, and external demand. Indeed, by introducing the role of exports in the profit function we can now investigate the general equilibrium effect of drought.

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 simulation experiments confirm that future domestic trade will act as an efficient mechanism to mitigate future weather conditions as its presence shifts an expected \$11.2 billion nationwide loss in profit into a \$3.3 billion gain compared to the current level. Therefore, domestic trade is a crucial factor in a country's capacity to cope with climate change and mitigate the risks associated to future food security.

In order to shed some light on the links between droughts, trade and agricultural profits within the United States, the next section provides some background information about the interstate agricultural trade flows, their database, and goes through an example demonstrating their sensitivity to severe drought. Section III provides the theoretical background and divides it into two subsections, one devoted to the gravity model and one to the Ricardian model, that describe our identification strategy. Section IV lists the remaining data and their sources. Estimation results as well as robustness tests and simulations results are presented in Section V. Finally, Section VI summarizes the results and offers some concluding remarks.

II. Intra-national Trade of Major Crops in the U.S.

This section first introduces the domestic trade datasets and then offers a snapshot of the agricultural trade flows within the U.S. It ends up with some intuitive perspectives regarding the changes in trade patterns under severe drought using modern data visualization tools.

II.A Data Sources for Domestic Trade Flows

To our knowledge, the only previous attempt to measure crop shipments across U.S. states was conducted by a team led by Lowell Hill. They conducted two nationwide surveys on the interstate movement of five major cereal grains in 1977 and 1985 (Fruin et al., 1990). Their surveys discontinued in the 1990s due to the publication of the commodity flow survey (CFS) that first appeared in the public domain in 1993. 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 its origin, destination, content, size, weight, dollar value and mode of transportation. Since its first publication, CFS has become the primary data source for domestic freight shipment studies (Wolf, 1997; Hillberry and Hummels, 2008; Crafts and Klein, 2014). While 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. The 2017 survey is still on-going at the time of writing this manuscript.

There are few caveats associated to 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 by 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 vs. 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 the more modern Freight Analysis Framework (Huwang et al., 2016) with the support of the Bureau of Transportation Statistics and the Federal Highway Administration (FHWA).

Currently in its fourth version, the Freight Analysis Framework (henceforth FAF4) data 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 towards foreign countries. Even though most of the final demand for agricultural products is located in metropolitan areas, intermediate demand, that is much larger, and the supply of such goods is not. As a result, we will focus on interstate trade in this manuscript. When it comes to disaggregation by commodity, FAF4 uses a two-digit sectoral classification of transported good (SCTG) that is similar to the harmonized system (HS) for international trade. Among the seven types of commodity available, we use *cereal grains* (SCTG 02) and *fruits, vegetables and oilseeds* (SCTG 03) only because they are constrained to the outdoor and thus they are more sensitive to extreme weather events than livestock and processed food which are the other two available categories. Note that soybean is the only major crop not listed in SCTG 02. It appears in SCTG 03, which obliges us to consider these two categories jointly in our manuscript even though fruits, vegetables and oilseeds represent only 36% of all these commodities (BEA, 2014). Robustness checks on each category will be performed anyway.

As mentioned in the introduction, the U.S. agricultural production and consumption are mostly for/from the domestic market. It is still true for grains, fruits, vegetables and oilseeds (henceforth "crops") but to a lower extent as 17.86% of the production is exported and 87.02% of the intermediate and final consumption is domestically grown (United Nations, 2017).

II.B A Snapshot of the Domestic Trade Patterns of Crops

<<Insert figure 1 here>>

Figure 1 represents the interstate trade flows in 2012, the most recent year available in the dataset. Panel (a) is a scatterplot showing for each state the value of crop export on the x-axis and the value of crop import on the y-axis (both in 2012 $ million). The size of the circle associated to each state is proportional to the value of its production of major crops while the three colors indicate the type of agricultural system (crop, animal or balanced) that is the most present in each state. The dotted lines represent the mean value of export and import. We find that California, Illinois, Iowa, Indiana, Minnesota, Missouri, New York and Nebraska are the "key" players in the interstate trade system (HH quadrant). The majority of these states are large crop producers, they have well-developed food-related industries and a large population. On the other hand, several states with low export but high import (LH) such as Texas, Wisconsin and Georgia are large livestock producers with a relatively small volume of crop grown locally. The high export – low import category (HL) is comprised of two types of states: i) the major producers of high-value crops (fruits, vegetables and greenhouse nursery products) such as New Jersey, Florida and Michigan and ii) the main crop producers with a small population density 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.

Panels (b) and (c) are heatmaps describing the 2012 trade patterns of the two SCTG categories used here. Different colors are used in each cell to represent the volume intensity of every 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. It confirms our expectations that the major driver of domestic trade is crops used for animal feed. Second, the "key" players identified in panel (a) emerge in the heatmap too. For instance, Illinois exports mainly corn and soybean to over 30 states, but it also imports various crops from the rest of the country due to its large food manufacturing industry and its specialization in a relatively small number of crops and vegetables.

II.C Changes in Trade Patterns Under Severe Drought: The Case Study of Nebraska

<<Insert figure 2 here>>

The two chord diagrams in figure 2 give us some additional insights about the potential impact of a drought on trade flows. They focus on Nebraska and its trade in 2007 (panel a) and 2012 (panel b). Nebraska is chosen because, according to the recent USDA census, agriculture occupies 92% of its land area, it contributes to around 30% of its GDP, the state ranks fourth in the nation in terms of agricultural sales and it is one of the primary producers of both cereal grains (it ranks fifth in the nation) and livestock meat (fourth in the nation). In addition, while Nebraska experienced virtually no drought-day in 2007, it was one of the most affected states 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 is 3.29, which indicates that Nebraska was clearly a net crop exporter that year. Second, California, Texas and Colorado are at the top of the 34 states Nebraska exported to while South Dakota, Kansas and Iowa are at the top of the 32 states Nebraska imported from.

Fast forward to 2012, the ratio of export to import is now 1.24. Nebraska exports to just 25 partners that year and the total exporting value has dropped by 9%. For instance, Nebraska stopped exporting to Pennsylvania and exports to Texas have decreased by 73% in value. At the same time, the number of importing partners slightly increased to 22 and the total importing value increased by 107%. The most drastic change compared to 2007 is the 362% increase in imports from Iowa.

To sum up, exports seem to be negatively impacted by a local drought while the opposite effect takes place for imports, as common knowledge would suggest. However, neither common knowledge nor the descriptive statistics used so far can tell us if droughts have a larger effect on imports or on exports. The structural gravity model we use to formally test this hypothesis is described in the next section.

III. Empirical Strategy

Our empirical strategy is based on the combination of two well-known reduced-form models, namely the gravity model of trade and the Ricardian model of climate change impact. This section decomposes this integrated methodology into three steps. The first step consists in estimating a gravity model focusing on the sensitivity of interstate trade to droughts and in extrapolating from it the (expected) equilibrium trade flows between U.S. states. Next, we aggregate all outward flows by origin state to measure the external demand they face and add it to our Ricardian model. Finally, we use the expected value of future weather conditions and droughts to estimate future agricultural profit when future interstate trade is included or disregarded. The difference between the two informs us about the capacity of trade to mitigate the damaging impact of future weather conditions on agricultural profit.

III.A Gravity Model of Interstate Agricultural Trade

Our starting point is the generalized structural gravity specification proposed by Head and Mayer (2014) which takes the following form:

$$X_{ijt} = \frac{Y_{it}}{\Pi_{it}} \frac{E_{jt}}{P_{jt}} \tau_{ij} \quad (2)$$

Where X_{ijt} is the bilateral trade flow from exporter *i* to importer *j* at time *t*. Exporter *i*'s features are represented by Y_{it}. Ideally, these features should describe state *i*'s potential for agricultural export. Therefore, besides the commonly used farm industry GDP, we also include other factors affecting agricultural productivity such as growing degree days (DD), precipitation (RN) and the drought conditions (DT) as follows:

$$Y_{it} = \exp\left(\beta_1 GDP_{it}^{fm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it}\right) \quad (3)$$

Similarly, E_{jt} represents importer *j*'s features. Its level of demand is captured through its GDP in food manufacturing, as the standard gravity model suggests, as well as other factors affecting its own agricultural production because fluctuations in the latter can affect demand for external goods. For instance, a drought is expected to increase the import of crops.

$$E_{jt} = \exp(\delta_1 GDP_{jt}^{fd} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt}) \quad (4)$$

In Eq. (2), the terms Π_{it} and P_{jt} are the multilateral resistance terms (MLRTs) for the exporter and importer respectively. Anderson and Van Wincoop (2003) argue that the existence of these MLRTs is the key distinction between the structural gravity and the naïve gravity that traces back to Tinbergen (1962). We approximate these multilateral resistance terms by 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)[2].

[2] We are aware that Yotov et al. (2016) have suggested to control for the MLRT by using exporter-time and importer-time fixed effects but this approach would obviously absorb the variables of interest.

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

$$\tau_{ij} = \exp\left(\pi_1 T_{ij} + \pi_2 C_{ij} + \pi_3 H_{ij}\right) \tag{5}$$

Where T_{ij} is the distance between exporter and importer measured as the travel time by trucks, C_{ij} is the contiguity dummy that takes on value 1 when states i and j share a border and 0 otherwise. Last but not least, H_{ij} is a dummy capturing the home-state effect (value is 1 only when i = j). This intrastate dummy first appeared in Wolf (1997) as a measure of the home-state effect in intra-national trade and has become a standard control since then.

Plugging Eqs. (3) - (5) into Eq. (2) results in Eq. (6) that can be estimated by Poisson Pseudo-Maximum Likelihood (PPML). According to Silva and Tenreyro (2006, 2011), the PPML estimator generates more robust results than the traditional OLS when the data of bilateral trade contains many zeros and/or 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).

$$\begin{aligned} X_{ijt} = \exp\big(&\beta_1 GDP_{it}^{fm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it} + \\ &\delta_1 GDP_{jt}^{fd} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt} + \\ &\pi_1 T_{ij} + \pi_2 C_{ij} + \pi_3 H_{ij} - \ln(\Pi_i) - \ln(P_j)\big) \end{aligned} \tag{6}$$

Trade theory (Yotov et al., 2016; Head and Mayer, 2014) enables us to draw some expectations on the direction of the coefficients in our reduced-form estimation equation. As usual in gravity models, a shared border, the home effect, the MLRTs, the exporter's production capacity and the importer's demand are expected to promote trade while distance should reduce it. Drought has a negative impact on local productivity, therefore it should reduce export and increase import to compensate for the loss in local supply. The expected sign of the other weather variables is undetermined because the marginal effects of these variables on agricultural productivity are not unambiguously positive or negative.

Before we close our discussion on the gravity model, we make a few remarks with regards to its fixed effect estimation as it has become standard practice since Feenstra (2015) proposed it as an alternative to the more complex calculation of MLRTs brought to the fore by Anderson and Van-wincoop's seminal paper (2003). Despite its popularity, the fixed effect estimation is not a silver bullet for every gravity model. One well-known limitation is that the origin- or destination- fixed effects absorb any monadic effect, i.e. any covariate that only varies by exporter (and are constant across all importers) or by importer (constant across all exporters). Unfortunately, our variable of interest, drought, is exporter- and importer-specific. Therefore, importer and exporter state-by-year fixed effects would absorb it. To bypass this issue, we approximate the remoteness index using Wei's (1996) approach[3] and we also incorporate two types of fixed effect structures constructed at the climate zone level (each zone encompasses between two and eleven states): (i) climate-zone dyadic fixed effects and year fixed effects; (ii) climate-zone dyadic fixed effect as well as importer and exporter climate-zone-by-year fixed effects.

III.B Ricardian Analysis for Drought Impact

When it comes to the Ricardian model, we adopt the reduced-form specification of Deschênes and Greenstone (2007) and provide several important modifications to it:

$$\mathrm{Y_{it}} = \theta \mathrm{DT_{it}} + \gamma \widehat{\mathrm{EX}}_{\mathrm{it}} + \mathrm{f(DD_{it}, RN_{it})} + \rho_1 \mathrm{PI_{it}} + \rho_2 \mathrm{PD_{it}} + \nu_{\mathrm{i}} + \nu_{\mathrm{cz_i t}} + \epsilon_{\mathrm{it}} \tag{7}$$

Where $\mathrm{Y_{it}}$ is the net profit (before tax and subsidy) of growing crops in state *i* and year *t* and $\widehat{\mathrm{EX}}_{\mathrm{it}} \equiv \sum_{\mathrm{j \neq i}} \widehat{\mathrm{X}}_{\mathrm{ijt}}$ represents the (log of) the predicted export using the estimated gravity equation (6). 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

[3] 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.

extent of the drought matters in this case as geographically narrow shocks have little to no impact on prices as each state is assumed to be a price taker. Therefore, one would expect a drought of that type to decrease the volume exported and the profit in the affected state while 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, then it would lead to higher prices which would cushion the fall in profits in the exporting places. Importing states would not have as much leeway on trade diversion and would have to face more expensive inputs.

In Eq. (7), the other variables, $\mathrm{DT_{it}}, \mathrm{DD_{it}}$ and $\mathrm{RN_{it}}$ share the same meaning as in Eq. (6). $\mathrm{f}(\cdot)$ is the quadratic functional form as the non-linear effect of these variables has been highlighted numerous times in the Ricardian literature (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007). $\mathrm{PI_{it}}$ is the (log of) per capita income and $\mathrm{PD_{it}}$ stands for population density. They 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 et al., 2005). We also include the state fixed effects ν_i to capture any time-unvarying factors such as the soil quality, altitude, topography and geographical location. Last but not least, the climate zone-by-year fixed effects ν_{cz_it}, 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 affected profoundly 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, the national corn price per bushel tripled from $2.28 in 2006 to $6.67 in 2012 while the fruit and vegetable price index increased by 11% only over the same period.

In summary, the presence of predicted exports in the Ricardian equation allows us to calculate the general equilibrium effect of drought on agricultural profit and to highlight its spatially heterogeneous nature. In the absence of such interregional effects, our estimate of the marginal effect of drought on agricultural profit would likely to suffer from a missing variable bias (Anselin, 1988; Le Sage and Pace, 2009) which would affect our results, our projections, and would suggest misleading mitigation and/or adaptation strategies.

IV. 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 a gravity equation (Eq. 6). 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 since 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 of 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 Bureau of Economic Analysis (BEA). 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), will be used as an additional exporter feature in one of the robustness checks. Last but not least, as indicated in section III, a set of weather characteristics, including the variable of interest, also belongs to this category. However, since these variables will also be used for capturing the importer's features and for the Ricardian analysis, we postpone their descriptions to the latter part of this section.

Importer's features --- we choose the GDP in food manufacturing (NAICS code No. 311) from BEA as a proxy for a state's capacity to purchase agricultural products from any origin state. Since 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 choice 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 agricultural productivity in both the exporters and the importers. They 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 (Ritchie and NeSmith, 1991; Schlenker *et al*., 2006). Meanwhile, we sum daily precipitation over the growing season (April 1st to September 30th, according to Deschênes and Greenstone, 2007) to get 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:

$$\text{(8)} \qquad \text{Severe drought days}_{\mathrm{s}} = \sum_{\text{c in state s}} \left\{ \underbrace{\left[\sum_{\mathrm{m}=1}^{12} \mathbf{1}\left(\mathrm{PDSI}_{\mathrm{c,m}} < -3\right) \right]}_{\text{count drought months}} \underbrace{\times\, 30}_{\substack{\text{convert}\\ \text{months}\\ \text{to days}}} \right\} \times \underbrace{\frac{\text{cropland}_{\mathrm{c}}}{\text{total cropland}_{\mathrm{s}}}}_{\substack{\text{weight by}\\ \text{county c's}\\ \text{cropland acreage}}}$$

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 (Eq. 8). They are the socioeconomic controls (population density comes from Census and per-capita income comes from BEA) and agricultural profit, the dependent variable. The latter corresponds to the (pre-subsidy) difference between the value of sales by crops farm and the correspondent 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 crops 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 up all the crop-related expenses to the universal expenses weighted by the value of sales by crop farms to all farms. Note that our approach is different from Deschênes and Greenstone (2007) as they calculate the difference between sales and cost of all farms instead of of crop farms alone. As a result, the set of activities farmers are choosing from when adapting to new weather conditions is limited to the various crops included in the trade flows and the profit function. Table 1 offers a summary of all the data used in this paper.

<<Insert table 1 here>>

V. Estimation Results, Robustness Checks and Impact Simulations

This section starts with the estimation results from the gravity equation and several robustness checks (subsection A). Then it continues with the calculation of the changes in the extensive and intensive margins of trade due to drought (B) as well as the marginal effects of drought in our general equilibrium Ricardian setting (C). Finally, it moves on to assessing the impact of future weather conditions on agricultural profit with and without trade (D).

V.A Estimation Results of the Gravity Equation

<<Insert Table 2 here>>

Table 2 reports the OLS and PPML regression results of Eq. (6) with the two fixed effect structures mentioned at the end of section III. By comparing the OLS estimates with the PPML estimates, we confirm that PPML is the preferred estimation method. Indeed, the presence of zero flows causes OLS to eliminate around one third of the observations as the dependent variable is in log terms, and the corresponding adjusted R squared to be significantly lower than in PPML. We also find that there are only minor differences in the PPML coefficient estimates based on the two sets of fixed effects. Therefore, we choose column (4) as the preferred specification because its fixed effect structure is more consistent with the theory (Yotov et al. 2016) than the one used in column (3).

The coefficient estimates from our preferred specification confirm our intuitions behind the changes in trade flows seen in Nebraska in 2012 compared to 2007. Indeed, our results confirm that severe drought days in the origin state have a negative impact on export because they reduce the state's supply capacity. Yet, this effect is not statistically significant, even at 10%. More drought days in the destination state, on the other hand, increase that state's demand for outside agricultural commodities. Importing flows are therefore more sensitive to droughts than exporting flows (even if origin-drought days were significant, the difference with destination-drought days would be significant at 5% according to a Wald test). 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 as a way to compensate for the current year's limited production. On the demand side, however, the food industry in the destination state enjoys much less flexibility. Indeed, in the event of a local drought, it becomes more dependent on imported inputs because the location of its food processing plants is fixed at least in the short- and medium-term. Similarly, it is reasonable to assume that other forms of demand, livestock, population and bioenergy facilities, do not move much across states.

Note that another causal interaction between weather and trade is the significantly positive role of precipitation in the destination state on exports. Origin precipitation does not have a statistically significant impact on trade though. The rest of the covariates are significant, and their sign meets the theoretical 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 the trade theory suggests (Feenstra, 2015).

<<Insert Table 3 here>>

There are several confounding factors and caveats that might affect the validity of the key conclusions mentioned above. Table 3 presents a list of robustness checks that, to some extent, addresses these concerns and caveats. The first two deal with the fixed effects defined at the climate zone level. As mentioned in section III, the ideal fixed effect structure suggested by trade theorists involves importer-by-year and exporter-by-year fixed effects, but they would completely absorb any variation in drought conditions. We first test the robustness of our results by adopting 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 check uses one side exporter/importer-by-year fixed effects. When we try to identify the impact of drought in destination, the exporter-by-year fixed effects are included to absorb any origin-specific factors, meanwhile the other factors remain the same as in Eq. (6). Similarly, the impact of drought in the origin state is identified by replacing destination-specific factor in Eq. (6) with the importer-by-year fixed effects.

Another robustness check consists in testing the results when the two types of trade flows, cereal grain (SCTG 02) and other main crops (SCTG 03), are identified singularly. Indeed, one would expect that their individual sensitivity to drought differs since the fields growing cereal grains are more likely to be rain-fed than those growing fruits and vegetables.

The price effect may be a serious confounding factor. Since 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 to the use of the actual physical quantities of the interstate shipments. These data come from FAF[4].

Another potential identification problem comes from severe drought days that are measured for the entire year. Recent scientific studies (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) while the other one counts only the drought that occurred in the last three months of the growing season (July, August and September)[4].

[4] 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.

Finally, we examine the sensitivity of our results to the addition of other explanatory variables capturing the pull and push factors of the flows. Specifically, the crop stock left from the previous year can be considered as a potential contributor to the supply capacity of the origin state. Furthermore, besides the conventional use of major crops, 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, hence their role needs to be investigated too.

The coefficients and standard errors associated to drought are reported for each of the robustness checks above in table 3. These results confirm those displayed in table 2 in that drought has a negative but non-significant effect in the origin state while it has a positive and significant effect (at 5% at least) in the destination state.

V.B Drought Impacts on Extensive and Intensive Margin

We explore further how drought affects the extensive and intensive margins of the agricultural trade flows through the decomposition suggested by Chaney (2008). For this analysis, we report two timings of drought, full year and 3-month before harvest, as the results for the growing season are very similar.

<<Insert Figure 3 here>>

Figure 3 presents the regression results. Panel A is dedicated to the extensive margin (i.e. number of trade partners), panel B displays the intensive margin in monetary terms (million dollars per partner) while panel C shows the intensive margin in physical terms (kilotons 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, droughts reduce the extensive margin of the export flows. States experiencing a severe drought reduce the number of places they export to, more especially if they export grains. On the other hand, a drought in an importing state obliges it to increase its number of grains suppliers while the effect on imports of vegetables, fruits and oil seeds is mostly non-significant.

Panels B and C show 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 larger than the value of the extensive margin effect. When it comes to a drought in the destination state, the average effect on the intensive margin of grain export is positive and large at 0.1. It is nearly four times the extensive margin effect, so droughts affect the volume/value traded much more than the number of trade partners. We also note that these effects are asymmetric across commodities as the average intensive margins for trade in vegetable, fruit and oil seeds are close to zero.

V.C Marginal Effects Calculation

It follows from (7) that, unlike the case of the Ricardian model without interstate interaction, the derivative of $\mathrm{Y_i}$ with respect to drought does not equal θ only but takes a value determined by the i,j th element of the partial derivative matrix S below:

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

Based on the terminology introduced by LeSage and Pace (2009) for spatial interaction models, we define the average direct impact of a drought on profit as the average of S_{ii} or $\frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}\frac{\partial\, \mathrm{Y_i}}{\partial\, \mathrm{DT_i}} = \frac{1}{\mathrm{n}}\mathrm{tr}(\mathbf{S})$. Furthermore, while typical regression coefficients are interpreted as the average effect of the explanatory variable on the dependent variable over the sample of observations, our general equilibrium approach ensures that each of these diagonal derivatives is actually composed of the following elements:

$$\frac{\partial\, \mathrm{Y_i}}{\partial\, \mathrm{DT_i}} = \theta + \frac{\partial\, \mathrm{EX_i}}{\partial\, \mathrm{DT_i}} = \theta + \gamma \times \sum\nolimits_{\mathrm{j}} \frac{\partial\, \mathrm{X_{ij}}}{\partial\, \mathrm{DT_i}} = \theta + \gamma \times \beta_4 \times \frac{\mathrm{EX_i}}{\mathrm{DT_i}} \tag{9}$$

Equation (9) indicates that the first, direct, channel of transmission of a change in drought in *i* on profit in *i* comes from the partial differentiation of Eq. (7) 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 $\beta_4 = \frac{\partial \log(X_{ij})}{\partial \log(DT_i)}$.

In addition, the sum of the off-diagonal element of row *i* in matrix S corresponds to the interstate spillovers of drought on the agricultural profit of location i (inward effect). It represents the total impact on Y_i from changing the amount of droughts in any other state.

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

Similarly, the sum of the off-diagonal elements of column *i* in matrix S allows us to calculate how a drought in state *i* spills over all other locations (outward effect) and affects their agricultural profit.

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

<<Insert Figure 4 here>>

Figure 4 displays the direct effect (panel A), the inward spillover effect (panel B) and the outward spillover (panel C) of one extra week of severe drought on the per acre agricultural profit of each state. As expected, Panel A suggests the direct effect of a severe drought on profit is negative (Eq. 9). 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 profit loss than the rest of the country after one additional week of droughts.

Inward spillover effects, on the other hand, report that the average effect of one additional week of drought in the trade partners reduces their local production, obliges them to import from a given state, hence increases local profit. It can be seen from panel B that the Corn Belt states such as Iowa, Illinois and

North Dakota, and the other "key" players in the agricultural trade, California for example, are the ones that benefit the most from the distress of their trade partners.

Panel C illustrates the spatial distribution of the outward spillover effects which correspond to the average changes in the trade partners' agricultural profit arising from one extra week of drought in a given state. Our results show that Minnesota, Indiana and Washington are the top three states of which trade partners benefit the most from a drought in the former. 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 position in the interstate trade system.

V.D Future Projections

Finally, we conduct a simulation experiment of the impact of future weather conditions on future agricultural profit in order to illustrate the benefits of including interstate trade in the Ricardian framework. In the benchmark scenario we use the marginal effect of the weather variables, including drought, on profit calculated from a model without trade. In the alternative scenario, the trade-induced spillovers emanating from Eq. (6) are also accounted for. 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 in Eq. 6 and 7. It allows us to calculate the change in profit due exclusively to the expected change in weather conditions.

Based on our approach, interstate trade should be seen as an efficient adaptation mechanism if the losses in the predicted profit from the second scenario are lesser those derived from the trade-less scenario. Following the suggestion of Burke et al. (2016), four different future climate models are used 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[5]. 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 average temperature and precipitation these models generate to do our simulations. For changes in severe drought days, we adopt the self-calibrated PDSI data of Dai et al. (2017) which, in spite of its recent publication, has been used in several contributions to quantify the future drought patterns due to climate change (see Zhao et al. 2017, Huang et al., 2017, Trenberth et al., 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 is projected based on 14 different general circulation models (GCMs). We use the average of all 14 GCMs, calculate the average severe drought days for the base (1968-2000) and the future (2038-2070) periods using Eq. (8) and then take their difference. The average change in the nation 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.

<<Insert Figure 5 here>>

The difference in the results of our simulation experiments with and without trade are reported in figure 5. The map in Panel A displays for each state the magnitude of the expected capacity of interstate trade to mitigate the adverse effect of climate change on agricultural profit[6]. As expected, the magnitude of the mitigation is greater for the main crop producers and exporters of the Midwest. Among them

[5] 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.

[6] 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.

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 33 states should expect a $30 per acre or more mitigation effect due to trade. It represents as much as 15% of the average national farm profit measured over 1997-2012.

VI. Conclusion

This paper offers a novel reduced-form approach that incorporates the sensitivity of U.S. agricultural profit to the interregional trade of agricultural commodities which, in turn, is sensitive to the occurrence of severe drought in the destination states and, to a lesser extent, in the origin states too. This general equilibrium approach allows the marginal effect of a drought on the profit of each state to differ spatially depending on the state's position in the domestic trade system of agricultural commodities. For instance, we find that the major crop producer and exporter states such as Illinois, Minnesota and Indiana are the main beneficiaries of the distress a drought generates in their trade partners.

In order to reach these results, we first highlight that droughts increase the import of commodities and reduce export although the latter effect is not statistically significant. Importing flows are less resilient to extreme weather events because the spatial location of their demand, whether it is the food manufacturing sector, live animals or households, is fixed. The estimates of our structural gravity model allow us to calculate the expected value of the interstate exports of agricultural commodities. It is integrated into a spatially explicit Ricardian model of which results indicate that the indirect effect of droughts through changing trade flows has a larger impact on a state's agricultural profit than its direct, local, effect. Further investigation reveals that the intensive margin of traded grains, whether measured in volume and value, is more affected than their extensive margin.

Whether trade can serve as a successful mitigation mechanism is one of the challenging questions the uncertainty associated to future weather conditions oblige us to investigate further. While the evidence at the international level seems promising (Reilly and Hohmann, 1993; Rosenzweig and Parry, 1994; Julia and Duchin, 2007; Schenker, 2013), this manuscript is the first one to deal with intranational trade where the capacity of adaptation is limited by the range of nationally-produced goods, country-wide weather conditions and the national transportation network. However, the advantage of studying domestic trade is that the confounding effect of the traditional international trade barriers is removed. Moreover, the size of the U.S. domestic market as well as the White House's reconsideration of several international trade agreements obliges us to prioritize the domestic rather than the international trade to evaluate the future of the nation's food security.

Based on precipitation and rainfall data derived from four combinations of future regional and global climate models as well as future drought data projected from 14 different general circulation models (Dai et al., 2017), our results indicate that the capacity of domestic trade to mitigate the adverse effect of future weather conditions is worth $ 14.5 billion (in 2012 prices). Indeed, while a $ 11.2 billion nationwide loss in agricultural profit is expected when trade is disregarded from our model, its presence turns our projections into a $3.3 billion gain or a 3.4% percent increase in annual agricultural sector profit. This figure is close to the 4% annual gains expected in Deschênes and Greenstone (2007) even though they do not consider trade. Far from claiming that trade is the "silver-bullet" answer to the adverse effect future weather conditions are expected to produce, our results challenge the relevance of the future estimates generated by the current Ricardian literature where agricultural profit (or farmland values when cross-sections are used) is independent of the changes in weather conditions (or climate in cross-section) in the places importing agricultural commodities.

Future research could take our general equilibrium approach in several directions. First, one could consider the trade flows of all agricultural activities, including livestock, as a way to come closer to the traditional Ricardian measurements where all sectors are bundled up. This approach could then consider higher order effects such as when the sale of crops used for animal feed affects the interstate trade of live animals to the food manufacturing industry. We anticipate that this approach would conclude to an even larger capacity of the domestic trade to mitigate the effect of future weather conditions on agricultural profit. Second, our results provide some useful insights to 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 it (Ziska et al., 2016). Third, 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. Smith and Lazo, 2001; Gu et al., 2008; Zhang et al., 2013; Kukal and Irmak, 2018).

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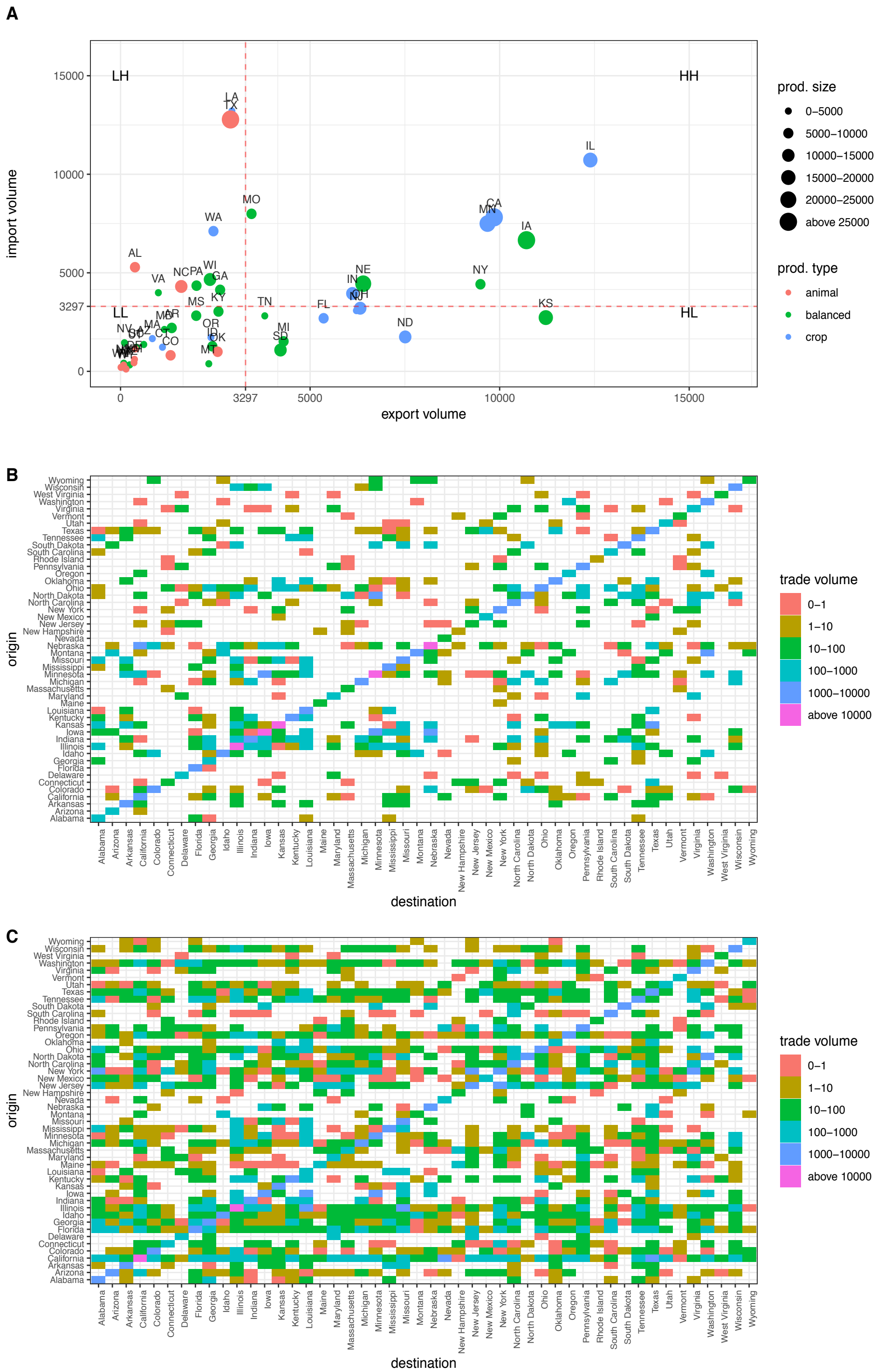
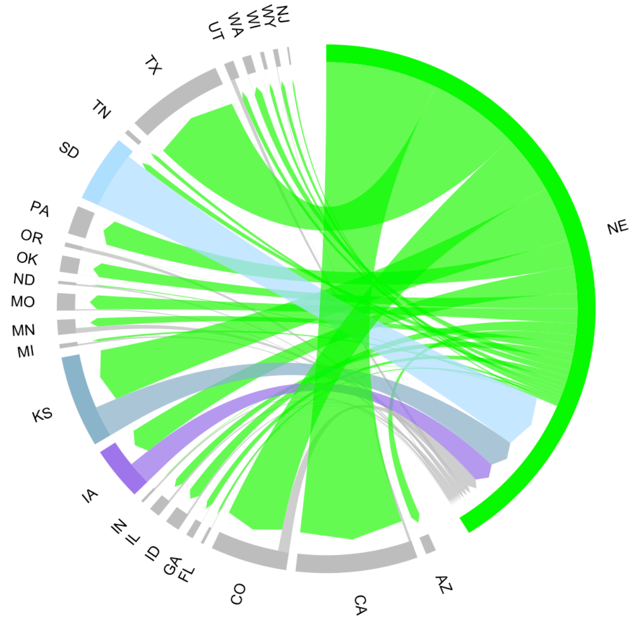


FIGURE 1. OVERVIEW OF DOMESTIC TRADE FLOWS OF MAJOR CROPS IN 2012

A



B

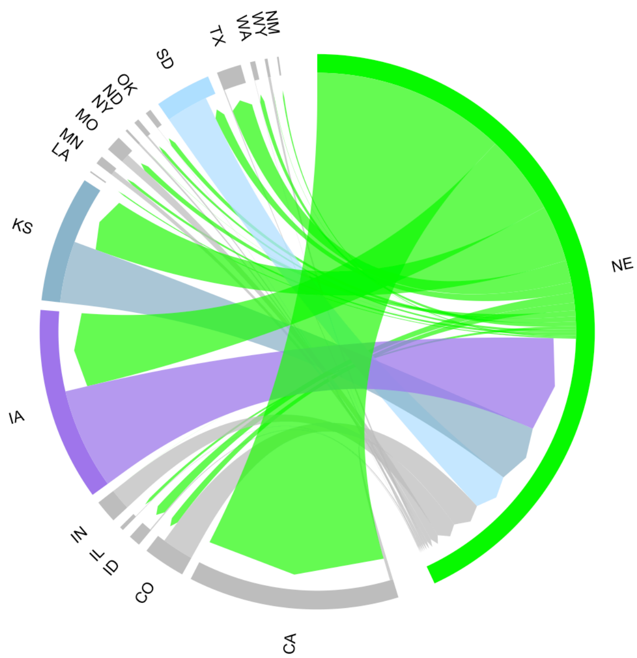


FIGURE 2. CHANGES IN TRADE FLOWS UNDER SEVERE DROUGHT: NEBRASKA

Notes: The chord diagrams show the trade flows from/to Nebraska in 2007 when the state experienced regular weather conditions (panel A) and in 2012 when it suffered from a severe drought (panel B).

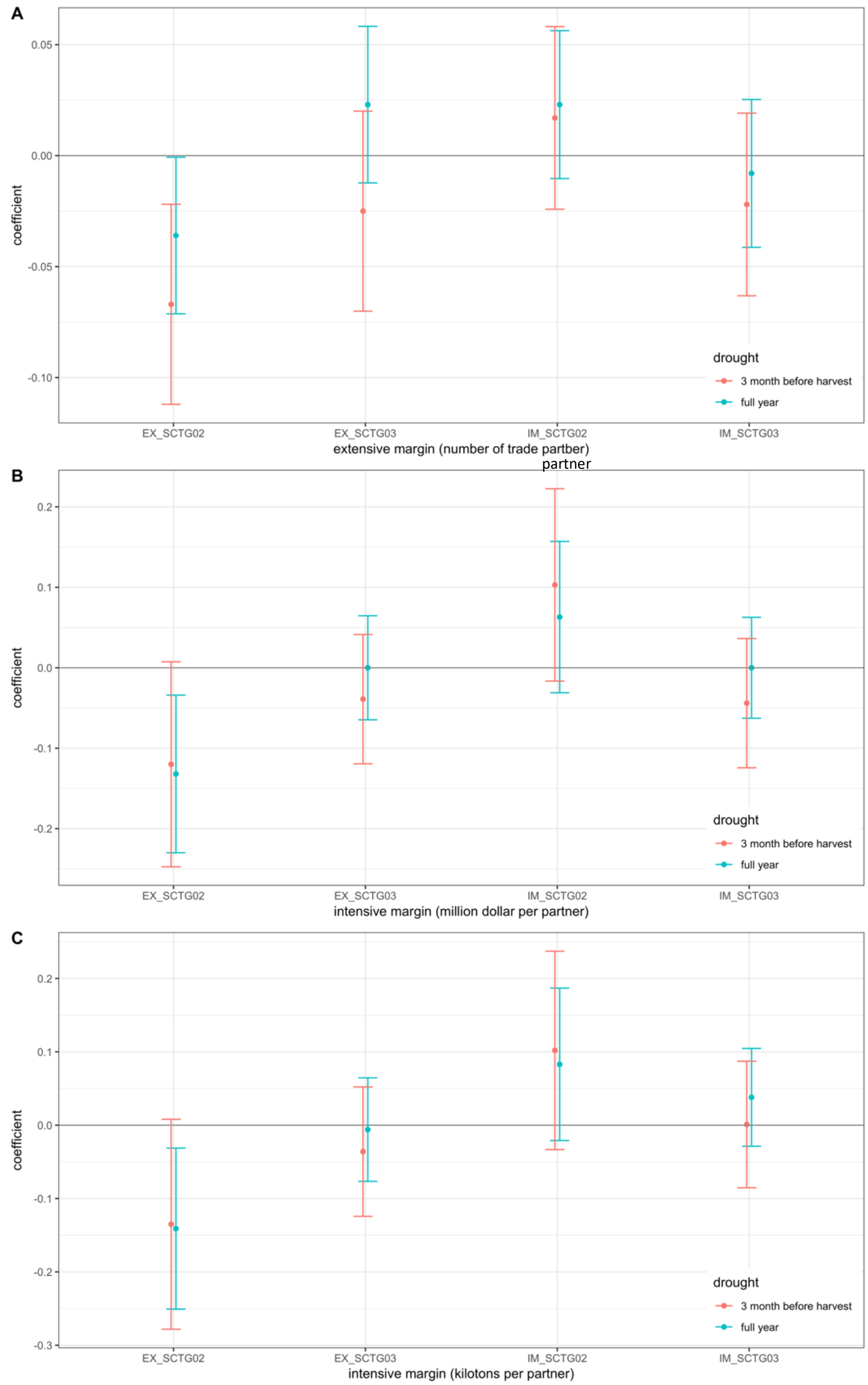


FIGURE 3. RESULTS FOR THE EXTENSIVE AND INTENSIVE TRADE MARGINS

Notes: The figure shows the point estimates (with the 95% confident interval) of the severe drought impact on the extensive margins (panel A) and intensive margins in monetary terms (panel B) and intensive margins in physical terms (panel C) of agricultural trade flows. artner

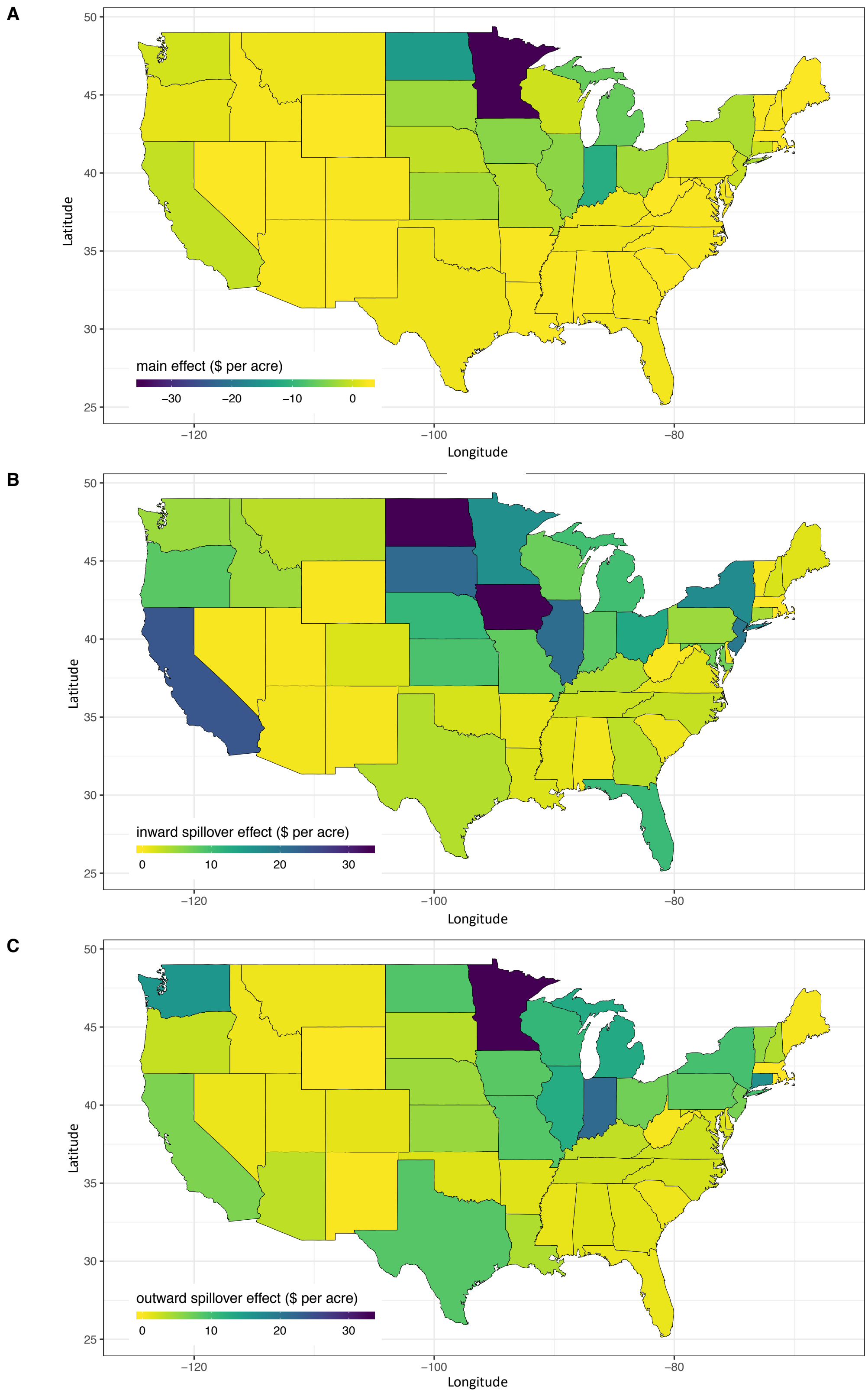


FIGURE 4. AVERAGE OF THE DIRECT EFFECT (A), INWARD SPILLOVER EFFECT (B) AND OUTWARD SPILLOVER EFFECT (C) OF ONE ADDITIONAL WEEK OF SEVERE DROUGHT

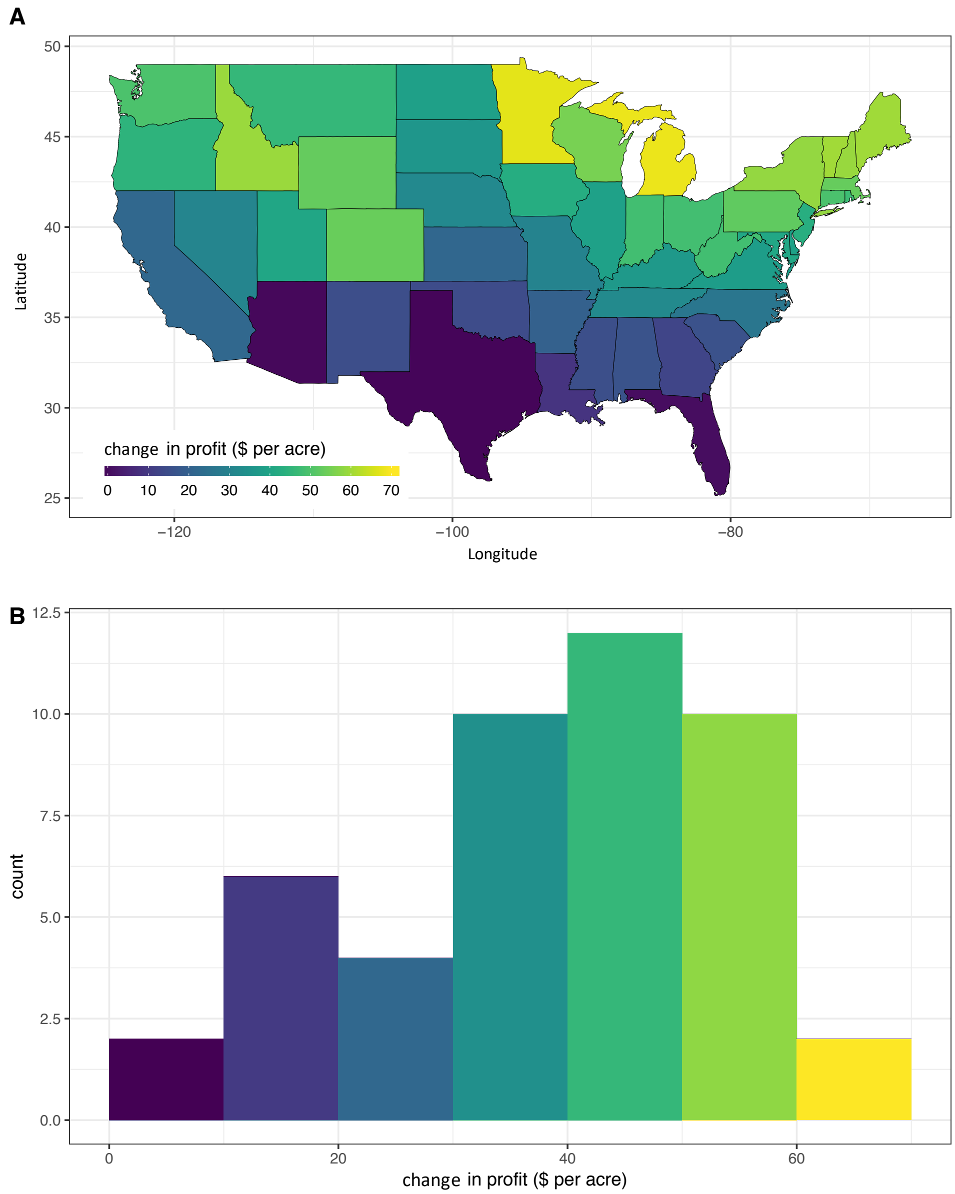


FIGURE 5. THE AVERAGE MITIGATION EFFECT OF TRADE

Notes: The figure shows the map and histogram of average mitigation effect of trade over four different climate models.

TABLE 1 — DATA SOURCES AND DESCRIPTION

Notation	Description	Sources	Usage
X_{ij}	Interstate trade flows of agricultural goods	FAF[4]	Gravity equation (dep. var.)
T_{ij}	Travel time between the most populous cities	Shapefile	Gravity equation
C_{ij}	Common boarder 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

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

TABLE 2 — ESTIMATION RESULTS FOR THE GRAVITY EQUATION (6)

	OLS		PPML	
	(1)	(2)	(3)	(4)
Common Border	1.611**	1.617**	1.015**	1.006**
	(0.153)	(0.154)	(0.227)	(0.227)
Travel Time	-1.920**	-1.911**	-0.607**	-0.631**
	(0.134)	(0.134)	(0.118)	(0.115)
Drought Days (Orig.)	-0.044+	-0.061+	-0.030	-0.029
	(0.026)	(0.033)	(0.025)	(0.032)
Drought Days (Dest.)	0.055*	0.002	0.069**	0.089*
	(0.027)	(0.033)	(0.026)	(0.036)
GDP (Orig.)	1.358**	1.366**	0.772**	0.781**
	(0.045)	(0.046)	(0.089)	(0.095)
GDP (Dest.)	1.026**	1.024**	0.456**	0.458**
	(0.039)	(0.039)	(0.051)	(0.051)
Remoteness Index (Orig.)	2.650**	2.694**	1.152*	1.189**
	(0.410)	(0.416)	(0.455)	(0.460)
Remoteness Index (Dest.)	3.208**	3.291**	0.446	0.630
	(0.423)	(0.451)	(0.639)	(0.729)
Degree Days (Orig.)	-0.021	0.019	0.150	0.117
	(0.273)	(0.282)	(0.348)	(0.371)
Degree Days (Dest.)	0.874**	1.021**	0.535	0.597
	(0.255)	(0.271)	(0.357)	(0.382)
Precipitation (Orig.)	-0.347*	0.008	-0.148	-0.144
	(0.149)	(0.203)	(0.170)	(0.255)
Precipitation (Dest.)	0.199	0.419*	0.505**	0.723**
	(0.150)	(0.211)	(0.190)	(0.257)
Home by year FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Climate region dyadic FE	Yes	Yes	Yes	Yes

Climate region by year FE (exporter and importer)	No	Yes	No	Yes
Num. of obs.	6401	6401	9216	9216
Adj. R squared	0.551	0.568	0.827	0.834

Notes: Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$.

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)	-0.02	(0.03)	0.06*	(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 of growing season	-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)

Notes: Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$.