THE ROLE OF INTERSTATE TRADE AND CROP INSURANCE PROGRAMS ON THE U.S. AGRICULTURE'S CAPACITY TO ADAPT TO CLIMATE CHANGE

BY

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DISSERTATION

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ABSTRACT

This dissertation presents three essays related to the economics of agricultural policies and climate change. The first essay discusses the relationship between interstate trade and the mitigation of native impacts caused by increasing frequency of severe droughts due to climate change. I combine two commonly used reduced form models: gravity equation and Ricardian analysis to study how drought will affect the domestic trade flow, and further change local agricultural profit. I find that interstate trade, to a large extent, can mitigate the adverse impact of increasing droughts towards U.S. agriculture. The second essay studies the potential impacts of federal crop insurance program on farmers' adaptation behavior. I extend the standard Ricardian framework to incorporate crop insurance. This extended Ricardian framework allows me to generate theoretical predictions on the changes in marginal effects of climate variable due to crop insurance. The empirical study using the most recent agricultural census data confirms the theoretical model. The third essay focuses on the misrating phenomenon in the federal crop insurance program (FCIP). This essay is the first attempt in the literature to formally quantify the scale of misrating issue, to study the spatial pattern of misrating status and to evaluate the fiscal impact of correcting the misrating in the program. The results suggest that the misrating is a large-scale phenomenon in FCIP, the misrating status possess a strong positive spatial autocorrelation pattern, and the correcting misrating can reduce the total outlay of the program but under very strict elasticity conditions for the demand of crop insurance.

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To my parents: Xiuzhen Zhang and Huadi Chen

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INTRODUCTION

The 2018 Nobel Memorial Prize in Economic Science was awarded to Yale Economist William Nordhaus "for integrating climate change into long-run macroeconomic analysis". Climate change has been recognized by the global society is a direct threat to the humanity in the 21st century. Meanwhile, increasing academic attention has been draw towards building a better understanding of its consequence, mitigation and adaption.

Agriculture, arguably the oldest industry in human history is, considered by many, one of the most vulnerable economic sectors under adverse climate change. Unlike other sector such as manufactory or service, the agricultural productivity despite thousand years' innovation, is still largely depends on weather conditions. As an old Chinese saying goes, "farmers are at the mercy of the forces of nature." (靠天吃饭). In 1994, Dr. Nordhaus and two coauthors (Mendelsohn and Shaw) published the path-breaking contributions studying the socioeconomic impact of climate change on agricultural sector in one of top economics journals: *American Economic Review*. (Mendelsohn et al. 1994) Since then, economists' passion about the topic has never faded away.

This dissertation is comprised of three closely-related chapters dedicating to understand how agricultural trade and federal crop insurance program could affect both the socioeconomic impacts of climate change and farmer's adaptation towards this challenge in U.S. agriculture. The story line goes as follows: The first chapter tells the bright side of the story. I study how domestic agricultural trade could help to successfully mitigate the adverse impacts of severe drought, which has been regarded as the most dangerous natural disaster to farming industry. Then, the second and third paper tell the other side of the story: crop insurance might discourage farmers' self-adaptation behavior against unfavorable changes in climate patterns, such as the increasing exposure to heat-stress days and severe droughts. In particular:

Chapter 1 assesses the efficiency of using interstate trade as a mitigation strategy towards the negative impacts of climate change on agricultural profit. 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.

Chapter 2 employs the Ricardian approach to study the relationship between crop insurance and adaptation to climate change. Federal crop insurance program (FCIP) is the cornerstone of the U.S. farm safety net programs. However, many have started to criticize the role of crop insurance programs in modifying the farmers' incentive to adapt to new climate conditions over the recent years due to the increasing awareness of the presence and outcomes of climate change. To address this question, a theoretical model is established by incorporating the crop insurance into the standard Ricardian framework. Then, the predictions generated by the theoretical model is tested using data capturing the climatic, economic and geophysical characteristics of the continental U.S.

counties over the four most recent USDA censuses. Our regression results highlight the marginal effect of the climate variables on farmland value is conditional upon a farmer's loss probability. These estimates are robust to numerous specification checks.

Chapter 3 documents the scales, spatial patterns and fiscal impacts of misrating phenomenon in the current federal crop insurance program (FCIP). As demonstrated in Chapter 2, misrated crop insurance policies, which premium fails to reflect the actual risk of a loss, might discourage farmer's self-adaptation behavior towards climate change. Even though several previous authors have speculated that the current ratemaking system is disproportionally in favor of the riskier areas, a formal study of the scale, spatial pattern and fiscal impacts of the misrating phenomenon is still missing in the literature. This chapter offers to fill this gap by analyzing over 2 million actuarial records collected by USDA's risk management agency since 1989, we discover that i) the issue of misrating prevails in the FCIP, ii) that counties with similar misrating statuses are clustered in space, and iii) that the fiscal implication of correcting misrating depends on the demand elasticity for insurance.

CHAPTER 1:

THE U.S. INTERSTATE TRADE WILL OVERCOME THE NEGATIVE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL PROFIT

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.

1.1 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

[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.

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, 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.

1.2 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.

1.2.1 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).

1.2.2 A Snapshot of the Domestic Trade Patterns of Crops

Figure 1.1 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.

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

The two chord diagrams in figure 1.2 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.

1.3 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.

1.3.1 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:

$$X_{ijt} = \frac{Y_{it}}{\Pi_{it}} \frac{E_{jt}}{P_{jt}} \tau_{ij} \qquad (1.1)$$

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:

$$Y_{it} = \exp\left(\beta_1 GDP_{it}^{fm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it}\right) \tag{1.2}$$

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.

$$E_{jt} = \exp(\delta_1 GDP_{jt}^{fd} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt}) \tag{1.3}$$

In Eq. (1.1), 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].

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

$$\tau_{ij} = \exp\left(\pi_1 T_{ij} + \pi_2 C_{ij} + \pi_3 H_{ij}\right) \tag{1.4}$$

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

[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.

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. (1.2) - (1.4) into Eq. (1.1) results in Eq. (1.5) 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).

$$\begin{aligned} X_{ijt} = \exp\,(&\beta_1 GDP_{it}^{fm} + \beta_2 DD_{it} + \beta_3 RN_{it} + \beta_4 DT_{it} + \\ &\delta_1 GDP_{jt}^{fd} + \delta_2 DD_{jt} + \delta_3 RN_{jt} + \delta_4 DT_{jt} + \\ &\pi_1 T_{ij} + \pi_2 C_{ij} + \pi_3 H_{ij} - \ln(\Pi_i) - \ln(P_j)) \end{aligned} \tag{1.5}$$

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.

1.3.2 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:

$$(1.6) \qquad Y_{it} = \theta DT_{it} + \gamma \widehat{EX}_{it} + f(DD_{it}, RN_{it}) + \rho_1 PI_{it} + \rho_2 PD_{it} + \nu_i + \nu_{cz_i t} + \epsilon_{it}$$

Where Y_{it} is the net profit (before tax and subsidy) of growing crops in state *i* and year *t* and $\widehat{EX}_{it} \equiv \sum_{j \neq i} \widehat{X}_{ijt}$ represents the (log of) the predicted export using the estimated gravity equation, Eq. (1.5). 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 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

[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.

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. (1.6), the other variables, $\mathrm{DT_{it}}$, $\mathrm{DD_{it}}$ and $\mathrm{RN_{it}}$ share the same meaning as in Eq. (1.5). $\mathrm{f}(\cdot)$ 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 $\nu_{cz_i t}$, 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 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.

1.4 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. (1.5). 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:

$$\text{Severe drought days}_s = \sum_{\text{c in state s}} \left\{ \underbrace{\left[\sum_{m=1}^{12} \mathbf{1}\left(\text{PDSI}_{c,m} < -3\right) \right]}_{\text{count drought months}} \underbrace{\times 30}_{\substack{\text{convert}\\ \text{months}\\ \text{to days}}} \right\} \times \underbrace{\frac{\text{cropland}_c}{\text{total cropland}_s}}_{\substack{\text{weight by}\\ \text{county } c'\text{s}\\ \text{cropland acreage}}} \tag{1.7}$$

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. (1.6). 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 1.1 offers a summary of all the data used in this paper.

1.5 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).

1.5.1 Estimation Results of the Gravity Equation

Table 1.2 reports the OLS and PPML regression results of Eq. (1.5) 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).

There are several confounding factors and caveats that might affect the validity of the key conclusions mentioned above. Table 1.3 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. (1.5). Similarly, the impact of drought in the origin state is identified by replacing destination-specific factor in Eq. (1.5) 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].

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 1.3. These results confirm those displayed in table 1.2 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.

1.5.2 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

[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.

two timings of drought, full year and 3-month before harvest, as the results for the growing season are very similar.

Figure 1.3 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.

1.5.3 Marginal Effects Calculation

It follows from Eq. (7) that, unlike the case of the Ricardian model without interstate interaction, the derivative of 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:

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

Based on the terminology introduced by LeSage and Pace (2009) for spatial interaction models, we define the average direct impact of a drought on profit as the average of S_{ii} or $\frac{1}{n}\sum_{i=1}^{n} \frac{\partial Y_i}{\partial DT_i} = \frac{1}{n}\mathrm{tr}(\mathbf{S})$. 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:

$$\frac{\partial Y_i}{\partial DT_i} = \theta + \frac{\partial EX_i}{\partial DT_i} = \theta + \gamma \times \sum_j \frac{\partial X_{ij}}{\partial DT_i} = \theta + \gamma \times \beta_4 \times \frac{EX_i}{DT_i} \tag{1.8}$$

Equation (1.8) 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. (1.6) 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 $\beta_4 = \frac{\partial \log(X_{ij})}{\partial \log(DT_i)}$.

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.

$$(1.9) \qquad \sum_{j\neq i}^{n} \frac{\partial\, Y_i}{\partial\, DT_j} = \sum_{j\neq i}^{n} \gamma \times \frac{\partial\, X_{ij}}{\partial\, DT_j} = \sum_{j\neq i}^{n} \gamma \times \delta_4 \times \frac{X_{ij}}{DT_j}$$

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

$$(1.10) \qquad \sum_{j\neq i}^{n} \frac{\partial\, Y_j}{\partial\, DT_i} = \sum_{j\neq i}^{n} \gamma \times \frac{\partial\, X_{ji}}{\partial\, DT_i} = \sum_{j\neq i}^{n} \gamma \times \delta_4 \times \frac{X_{ji}}{DT_i}$$

Figure 1.4 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, refers to Eq. (1.8). 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.

1.5.4 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. (1.5) 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. (1.5) and (1.6). 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

[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.

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. (1.7) 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.

The difference in the results of our simulation experiments with and without trade are reported in figure 1.5. 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 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

[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.

effect due to trade. It represents as much as 15% of the average national farm profit measured over 1997-2012.

1.6 Conclusions

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).

Figures and Tables:

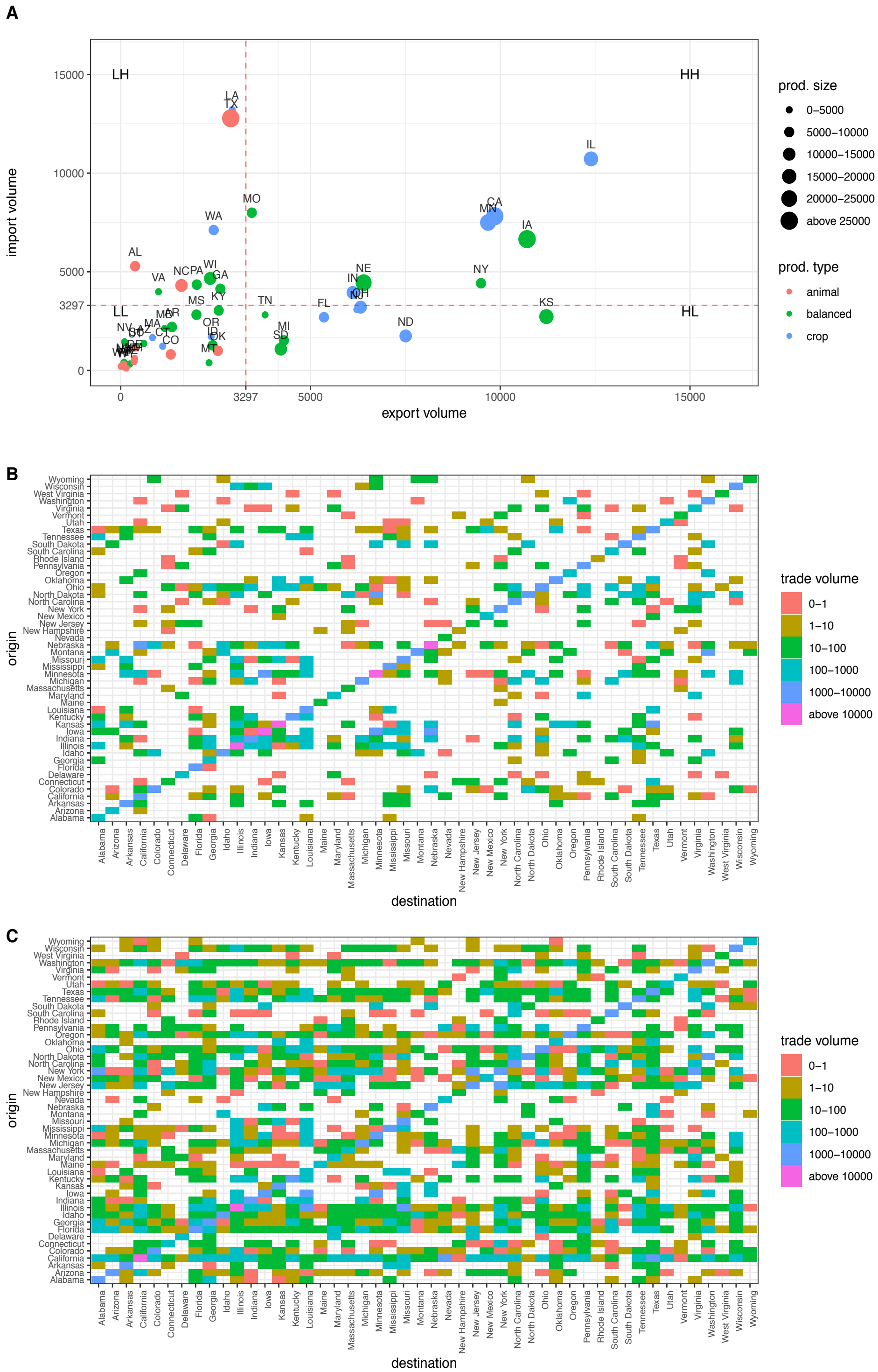
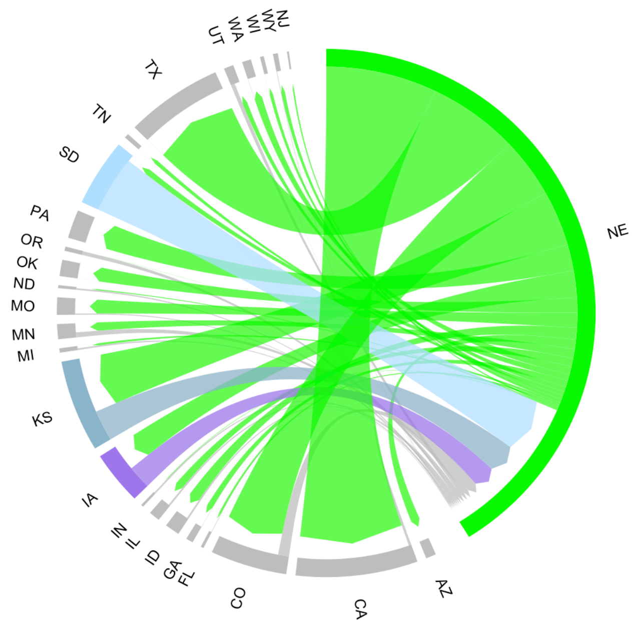


FIGURE 1.1 OVERVIEW OF DOMESTIC TRADE FLOWS OF MAJOR CROPS IN 2012

A



B

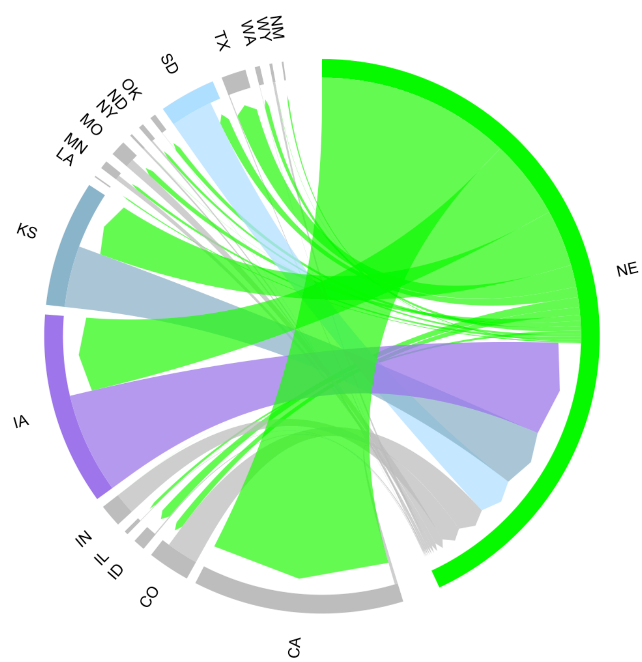


FIGURE 1.2 CHANGES IN TRADE FLOWS UNDER SEVERE DROUGHT: NEBRASKA

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).

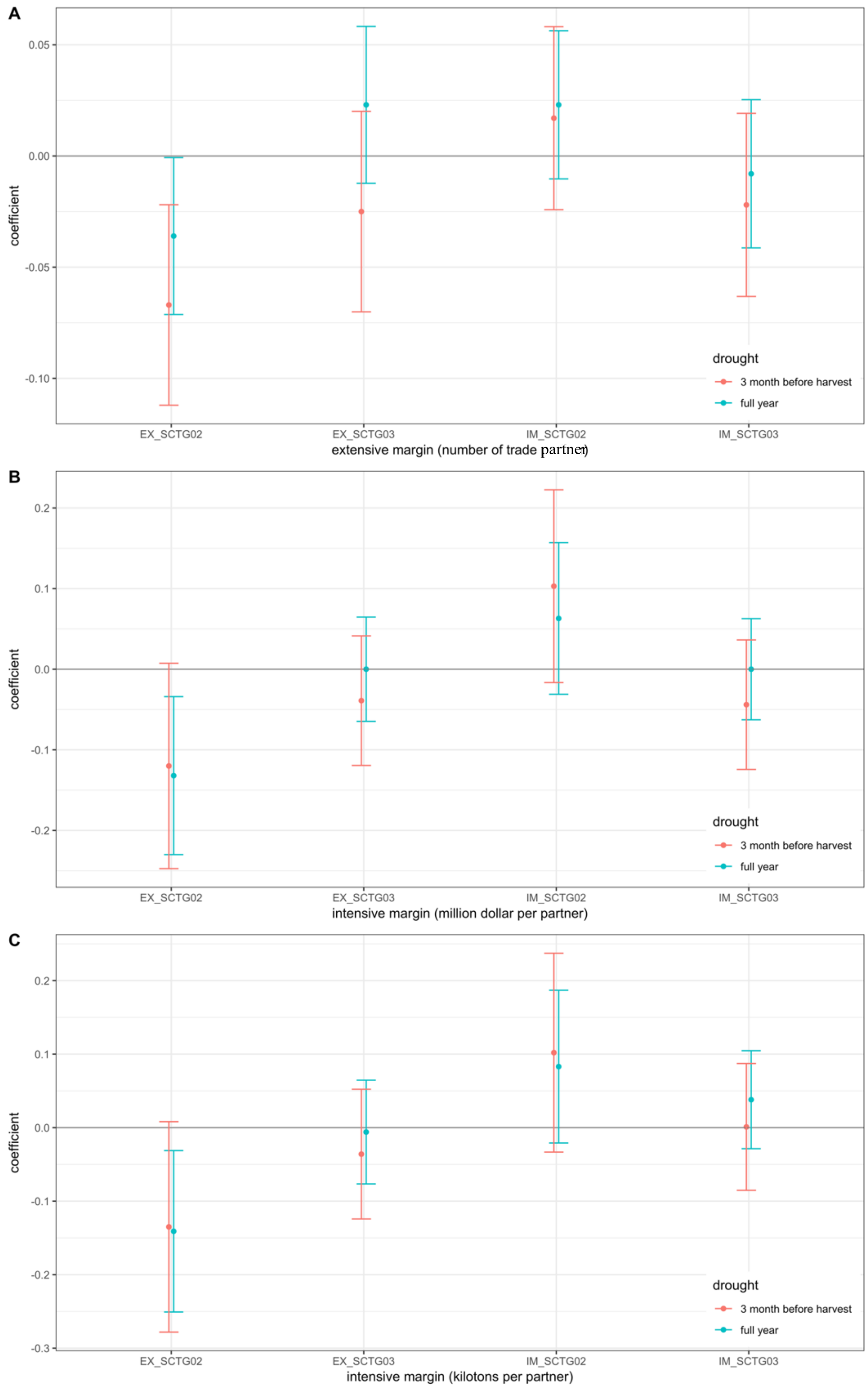


FIGURE 1.3 RESULTS FOR THE EXTENSIVE AND INTENSIVE TREAD MARGINS

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.

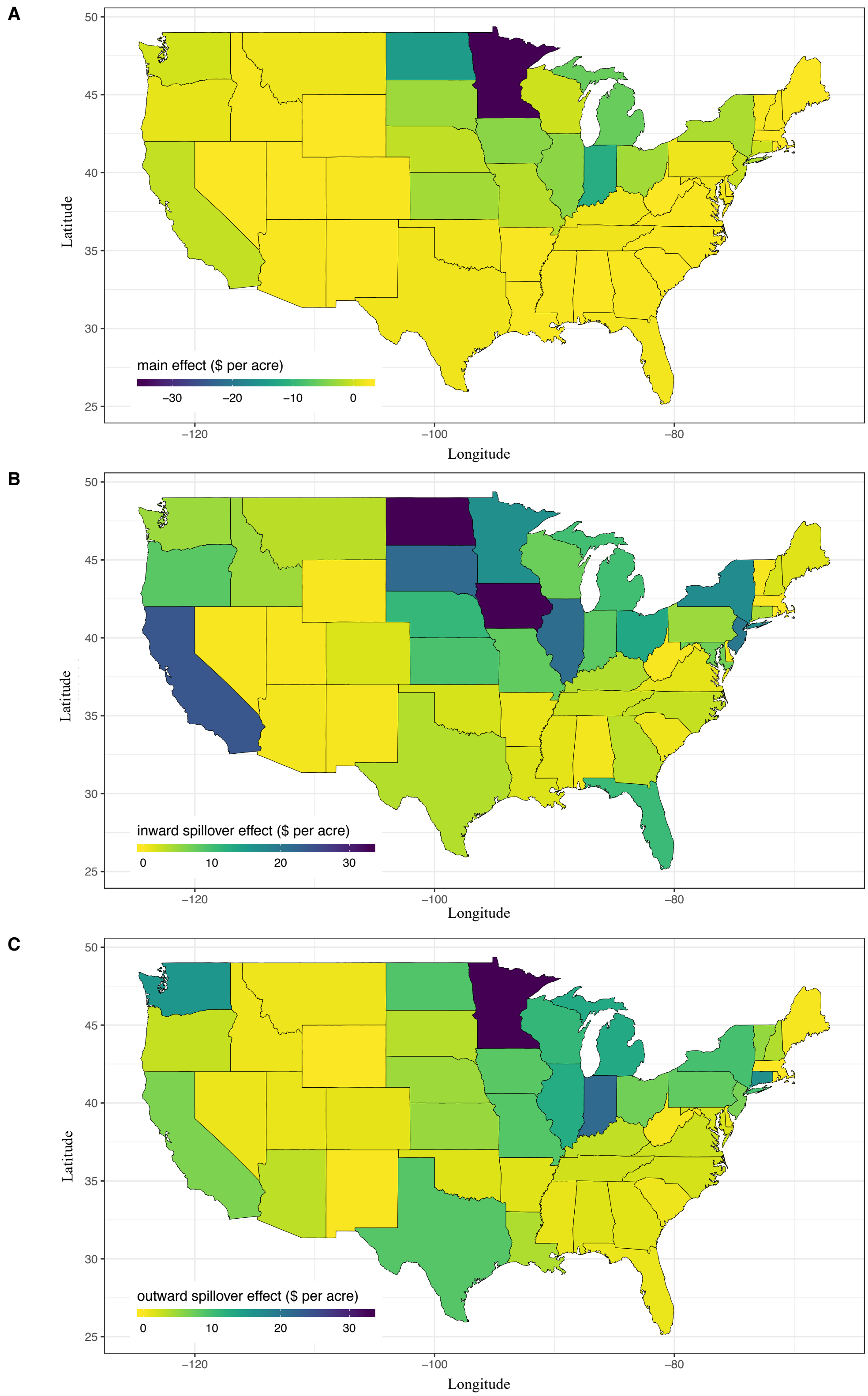


FIGURE 1.4 MAP OF MARGINAL EFFECTS DROUGHTS

Notes: the direct effect (panel A), inward spillover effect (panel B) and outward spillover effect (panel C) of one additional week of severe drought.

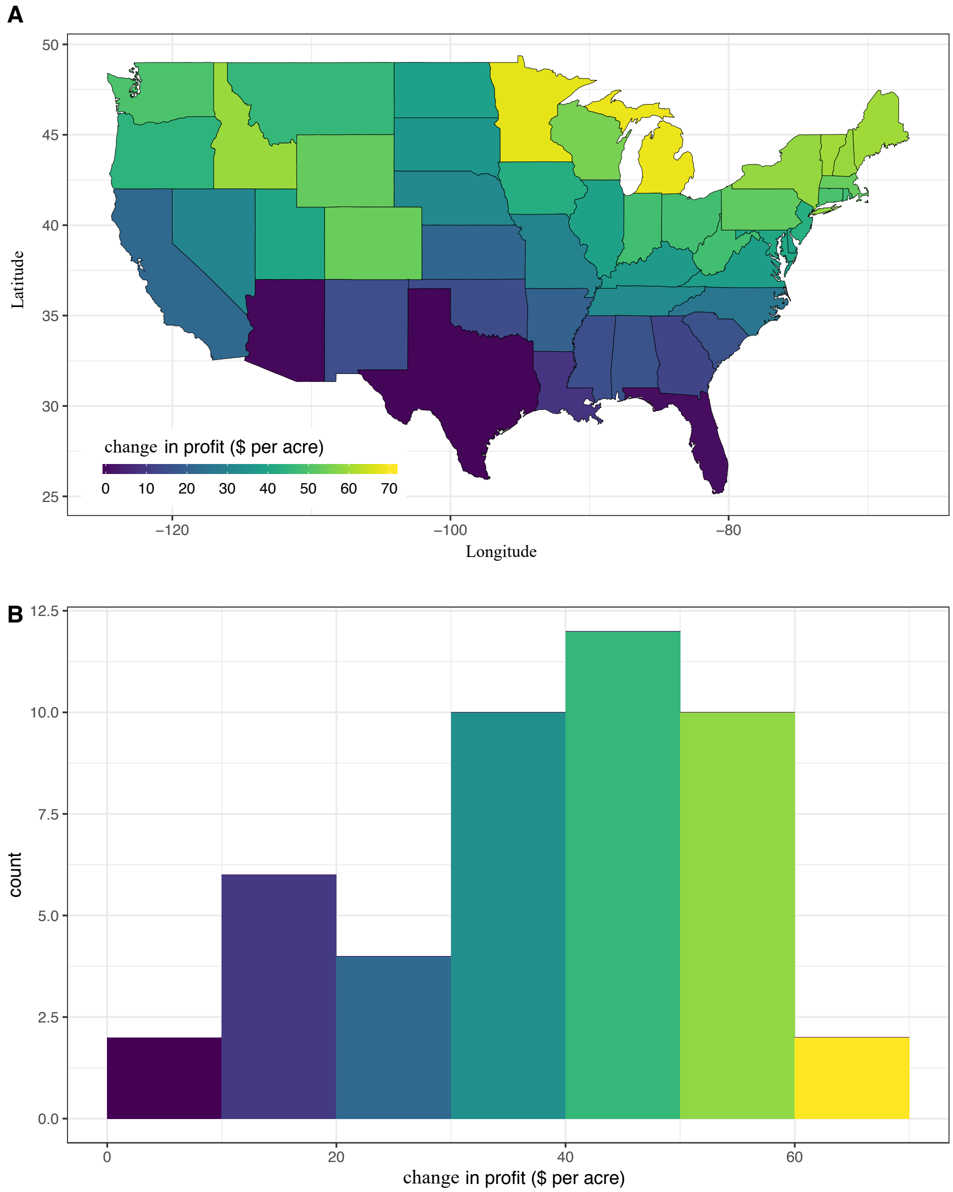


FIGURE 1.5 THE AVERAGE MITIGATION EFFECT OF TRADE

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

TABLE 1.1 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 Eq. (1.6) and (1.7).

TABLE 1.2 ESTIMATION RESULTS FOR THE GRAVITY EQUATION

	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 1.3 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, $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$.

References:

Anderson, James E., and Eric Van Wincoop. "Gravity with gravitas: a solution to the border puzzle." The American Economic Review 93, no. 1 (2003): 170-192.

Anselin, Luc. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers, Dordrecht, 1988

Arkolakis, Costas, Arnaud Costinot, and Andrés Rodríguez-Clare. "New trade models, same old gains?" The American Economic Review 102, no. 1 (2012): 94-130.

Bureau of Economic Analysis "Industry by industry total requirement table", 2014. https://www.bea.gov/industry/input-output-accounts-data.

Cho, Guedae, Ian M. Sheldon, and Steve McCorriston. "Exchange rate uncertainty and agricultural trade." American Journal of Agricultural Economics 84, no. 4 (2002): 931-942.

Chaney, Thomas. "Distorted gravity: the intensive and extensive margins of international trade." American Economic Review 98, no. 4 (2008): 1707-21.

Costinot, Arnaud, Dave Donaldson, and Cory Smith. "Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world." Journal of Political Economy 124, no. 1 (2016): 205-248.

Crafts, Nicholas, and Alexander Klein. "Geography and intra-national home bias: US domestic trade in 1949 and 2007." Journal of Economic Geography 15, no. 3 (2014): 477-497.

Dai, Aiguo, and Tianbao Zhao. "Uncertainties in historical changes and future projections of drought. Part I: estimates of historical drought changes." Climatic Change 144, no. 3 (2017): 519-533.

Deschênes, Olivier, and Michael Greenstone. "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather." The American Economic Review 97, no. 1 (2007): 354-385.

Feenstra, Robert C. Advanced international trade: theory and evidence. Princeton university press, 2015.

Ferguson, Shon, and Johan Gars. "Measuring the Impact of Agricultural Production Shocks on International Trade Flows." (2017) AAEA annual conference selected paper.

Fruin, Jerry, Daniel W. Halbach, and Lowell D. Hill. "Corn Movements in the United States: interregional flow pattern and transportation requirements in 1985" (1990) University of Illinois Bulletin 793

Grant, Jason H., and Dayton M. Lambert. "Do regional trade agreements increase members' agricultural trade?" American journal of agricultural economics 90, no. 3 (2008): 765-782.

Gu, Lianhong, Paul J. Hanson, W. Mac Post, Dale P. Kaiser, Bai Yang, Ramakrishna Nemani, Stephen G. Pallardy, and Tilden Meyers. "The 2007 eastern US spring freeze: increased cold damage in a warming world?." AIBS Bulletin 58, no. 3 (2008): 253-262.

Head, Keith, and Thierry Mayer. "Gravity equations: Workhorse, toolkit, and cookbook.", In Gopinath, Gita, Elhanan Helpman, and Kenneth Rogoff, eds. Handbook of international economics. Vol. 4. Elsevier, 2014.

Hillberry, Russell, and David Hummels. "Trade responses to geographic frictions: A decomposition using micro-data." European Economic Review 52, no. 3 (2008): 527-550.

Horridge, Mark, John Madden, and Glyn Wittwer. "The impact of the 2002–2003 drought on Australia." Journal of Policy Modeling 27, no. 3 (2005): 285-308.

Huang, J., Y. Li, C. Fu, F. Chen, Q. Fu, A. Dai, M. Shinoda et al. "Dryland climate change: Recent progress and challenges." Reviews of Geophysics 55, no. 3 (2017): 719-778.

Hwang, Ho-Ling, Stephanie Hargrove, Shih-Miao Chin, Daniel W. Wilson, Hyeonsup Lim, Jiaoli Chen, Rob Taylor, Bruce Peterson, and Diane Davidson. The Freight Analysis Framework Verson 4 (FAF4)-Building the FAF4 Regional Database: Data Sources and Estimation Methodologies. No. ORNL/TM-2016/489. Oak Ridge National Laboratory (ORNL), Oak Ridge, TN (United States), 2016.

IPCC. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 2014.

Jean, Sébastien, and Jean-Christophe Bureau. "Do regional trade agreements really boost trade? Evidence from agricultural products." Review of World Economics 152, no. 3 (2016): 477-499.

Julia, Roxana, and Faye Duchin. "World trade as the adjustment mechanism of agriculture to climate change." Climatic Change 82, no. 3-4 (2007): 393-409.

Kelejian, Harry H., and Gianfranco Piras. "Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes." Regional Science and Urban Economics 46 (2014): 140-149.

Kelly, David L., Charles D. Kolstad, and Glenn T. Mitchell. "Adjustment costs from environmental change." Journal of Environmental Economics and Management 50, no. 3 (2005): 468-495.

Krugman, Paul. Increasing Returns, Monopolistic Competition and International Trade, Journal of International Economics, 9, 4(1979): 469-479.

Kukal, Meetpal S., and Suat Irmak. "US Agro-Climate in 20 th Century: Growing Degree Days, First and Last Frost, Growing Season Length, and Impacts on Crop Yields." Scientific reports 8, no. 1 (2018): 6977.

Lippert, Christian, Tatjana Krimly, and Joachim Aurbacher. "A Ricardian analysis of the impact of climate change on agriculture in Germany." Climatic change 97, no. 3-4 (2009): 593.

LeSage, James, and Robert Kelley Pace. Introduction to spatial econometrics. Chapman and Hall/CRC, 2009.

Lobell, David B., Michael J. Roberts, Wolfram Schlenker, Noah Braun, Bertis B. Little, Roderick M. Rejesus, and Graeme L. Hammer. "Greater sensitivity to drought accompanies maize yield increase in the US Midwest." Science 344, no. 6183 (2014): 516-519.

Markusen, James R., James R. Melvin, Keith E. Maskus, and William Kaempfer. International trade: Theory and evidence. No. 21989. University Library of Munich, Germany, 1995.

McCorriston, Steve, and Ian M. Sheldon. "Intra-industry trade and specialization in processed agricultural products: The case of the US and the EC." Review of Agricultural Economics 13, no. 2 (1991): 173-184.

Mckee, T.B., Doesken, N.J. and Kleist, J. “The relationship of drought frequency and duration times scales”. American Meteorological Society. 8th Conference on Applied Climatology, 17-22 January (1993), Anaheim, 179-184.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. "The impact of global warming on agriculture: a Ricardian analysis." The American Economic Review 84, no. 4 (1994): 753-771.

Moore, Frances C., and David B. Lobell. "Adaptation potential of European agriculture in response to climate change." Nature Climate Change 4, no. 7 (2014): 610.

Qu, Xi, and Lung-fei Lee. "Estimating a spatial autoregressive model with an endogenous spatial weight matrix." Journal of Econometrics 184, no. 2 (2015): 209-232.

Reilly, John, and Neil Hohmann. "Climate change and agriculture: the role of international trade." The American Economic Review 83, no. 2 (1993): 306-312.

Reimer, Jeffrey J., and Man Li. "Yield variability and agricultural trade." Agricultural and Resource Economics Review 38, no. 2 (2009): 258-270.

Richie J.T. and NeSmith D. S. Temperature and Crop Development. In: Hanks J. and Ritchie J.T. (Eds.), Modeling Plant and Soil Systems, 5–29. Madison: American Society of Agronomy, 1991.

Rosenzweig, Cynthia, and Martin L. Parry. "Potential impact of climate change on world food supply." Nature 367, no. 6459 (1994): 133-138.

Salami, Habibollah, Naser Shahnooshi, and Kenneth J. Thomson. "The economic impacts of drought on the economy of Iran: An integration of linear programming and macroeconometric modelling approaches." Ecological Economics 68, no. 4 (2009): 1032-1039.

Sarker, Rakhal, and Sampath Jayasinghe. "Regional trade agreements and trade in agri-food products: evidence for the European Union from gravity modeling using disaggregated data." Agricultural Economics 37, no. 1 (2007): 93-104.

Schenker, Oliver. Exchanging Goods and Damages: The Role of Trade on the Distribution of Climate Change Costs, Environmental & Resource, 54, 2 (2013): 61-282.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. "The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions." Review of Economics and statistics 88, no. 1 (2006): 113-125.

Silva, JMC Santos, and Silvana Tenreyro. "The log of gravity." The Review of Economics and statistics 88, no. 4 (2006): 641-658.

Silva, JMC Santos, and Silvana Tenreyro. "Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator." Economics Letters 112, no. 2 (2011): 220-222.

Smith, Joel B., and Jeffrey K. Lazo. "A summary of climate change impact assessments from the US Country Studies Program." Climatic Change 50, no. 1-2 (2001): 1-29.

Sun, Lin, and Michael R. Reed. "Impacts of free trade agreements on agricultural trade creation and trade diversion." American Journal of Agricultural Economics 92, no. 5 (2010): 1351-1363.

Tinbergen, Jan, and A. Hekscher. Shaping the World Economy. Suggestions for an International Economic Policy. Twentieth Century Fund, 1962.

Trenberth, Kevin E., Yongxin Zhang, and Maria Gehne. "Intermittency in precipitation: Duration, frequency, intensity, and amounts using hourly data." Journal of Hydrometeorology 18, no. 5 (2017): 1393-1412.

United Nations Statistics Division. 2016 International Trade Statistics Yearbook, UN Comtrade, 2017.

Wang, Jinxia, Robert Mendelsohn, Ariel Dinar, Jikun Huang, Scott Rozelle, and Lijuan Zhang. "The impact of climate change on China's agriculture." Agricultural Economics 40, no. 3 (2009): 323-337.

Wei, Shang-Jin. Intra-national versus international trade: how stubborn are nations in global integration? No. w5531. National Bureau of Economic Research, 1996.

Wilhite, Donald A., "Chapter 1 Drought as a Natural Hazard: Concepts and Definitions" (2000). Drought Mitigation Center Faculty Publications. 69.

Wolf, Holger C. Patterns of intra-and inter-state trade. No. w5939. National Bureau of Economic Research, 1997.

World Input-Output Database, Database accessible at http://www.wiod.org/home. Database from Timmer M. P., Dietzenbacher E., Los B., Stehrer R. and de Vries G. J. (2015), An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production, Review of International Economics., 23 (2016): 575–605.

Yotov, Yoto V., Roberta Piermartini, José-Antonio Monteiro, and Mario Larch. An advanced guide to trade policy analysis: The structural gravity model. World Trade Organization, 2016.

y Pérez, L. Pérez, and J. Barreiro-Hurlé. "Assessing the socio-economic impacts of drought in the Ebro River Basin." Spanish journal of agricultural research 7, no. 2 (2009): 269-280.

Zhao, Tianbao, and Aiguo Dai. "Uncertainties in historical changes and future projections of drought. Part II: model-simulated historical and future drought changes." Climatic Change 144, no. 3 (2017): 535-548.

Zhang, Peng, Junjie Zhang, and Minpeng Chen. "Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation." Journal of Environmental Economics and Management 83 (2017): 8-31.

Zhang, Yongguang, M. Susan Moran, Mark A. Nearing, Guillermo E. Ponce Campos, Alfredo R. Huete, Anthony R. Buda, David D. Bosch et al. "Extreme precipitation patterns and reductions of terrestrial ecosystem production across biomes." Journal of Geophysical Research: Biogeosciences 118, no. 1 (2013): 148-157.

Ziska, Lewis, Allison Crimmins, Allan Auclair, Stacy DeGrasse, J. F. Garofalo, A. S. Khan, Irakli Loladze et al. "Ch. 7: Food safety, nutrition, and distribution." The impacts of climate change on human health in the United States: A scientific assessment (2016): 189-216

CHAPTER 2:

DO CROP INSURANCE PROGRAMS PRECLUDE THEIR RECIPIENTS FROM ADAPTING TO NEW CLIMATE CONDITIONS?

Abstract: This article employs the Ricardian approach to study the relationship between crop insurance and adaptation to climate change. We extend the basic Ricardian model to accommodate the presence of crop insurance and estimate it over a recent panel of the U.S. counties. The results indicate that federal crop insurance programs reduce the farmers' willingness to adapt to adverse changes in climate. We conclude that crop insurance programs need to be revisited as they have the potential to cause considerable social welfare loss in the long run.

Keywords: climate change, crop insurance, Ricardian approach

2.1 Introduction

The enactment of the Crop Insurance Reform Act of 1994 paved the way for crop insurance to become the main pillar of the current U.S. farm subsidy system. Two decades later, the Agricultural Act of 2014 confirmed the Congress's desire to keep expanding crop insurance programs to replace the direct payment programs. Today, crop insurance costs the American tax payers around seven billion dollars each year and accounts for roughly 30 to 40% of the annual total agricultural subsidies budget since 2010 (Environmental Working Group 2017).

The literature has already documented that crop insurance can distort the farmers' production decisions, such as his land allocation, his choice of crop mix and his optimal amounts of input use or of infrastructural investment (Goodwin and Smith 1995; Knight and Coble 1997; Coble and Knight 2002). However, increasing awareness of the presence and of the potential outcomes of climate change over the recent years has shifted the focus on the role of crop insurance programs in modifying the farmers' capacity to adapt to new climate conditions. For instance, Burke and Emerick (2015) highlight that they discourage U.S. corn and soybeans growers from being actively engaged in adaptation activities such as optimal uses of fertilizer and irrigation systems improvements. Indeed, these programs act as a moral hazard since farmers are aware that the government will compensate a large portion of the actual damages caused by unexpected weather events, whether linked to climate change or not. Anna and Schlenker (2015) provide additional evidence of such potential distortion effects in a crop production framework applied to the same two crops.

However, given that many other crops are grown in the country and that a farmer can always switch from one crop to another when new climate conditions emerge, a new framework is needed to investigate the role of crop insurance programs on climate change adaptation. Based on an extended version of the basic Ricardian framework (Mendelsohn et al. 1994; Schlenker et al. 2005; Schlenker et al. 2006; Deschênes and Greenstone 2007), our estimation strategy starts with measuring the loss probability, i.e. the frequency that a farmer receives supports from crop insurance programs. It carries on with a formal test of whether the marginal effect of the climate variables on a farmer's profit is sensitive to different probabilities of loss. Our conceptual model predicts that the sensitivity of the expected profit to changes in climate is lesser for the farmers that experience a higher loss probability. Indeed, the more frequently a farmer relies on indemnity to compensate for his loss, the less his net revenue correlates with his actual production characteristics. The same reasoning holds true for farmland value, the dependent variable traditionally used in a Ricardian framework, since it represents the discounted sum of future net revenues.

Based on data capturing the climatic, economic and geophysical characteristics of the continental U.S. counties over the four most recent USDA censuses, we test our theoretical predictions in a model capturing the interaction between loss probability and climatic variables. Our regression results highlight the marginal effect of the climate variables on farmland value is conditional upon a farmer's loss probability. These estimates are robust to numerous specification checks.

To our knowledge, there are only three contributions that formally model the impact of overall farm subsidy payments in a Ricardian framework. The first one is Polsky (2004) who highlights how overall subsidies have a small positive effect on farmland values in the Great Plains. The second one is Massetti and Mendelsohn (2011) who, for a panel measured across the entire sample of the U.S. counties, find a slightly negative marginal effect. This unexpected negative effect is probably caused by the endogeneity issue of subsidies that the authors fail to address.

Finally, Dall'erba and Dominguez (2016) focus on the South-Western part of the U.S. and, like Polsky (2004), find a small but significant positive effect of subsidies. Their article is the only one among the three to control for the endogeneity of the subsidy payments through a two-stage-least-square approach.

The current article distinguishes itself from the previous literature for three reasons. First, instead of pooling all forms of subsidies together, identifying the singular effect of crop insurance allows us to formally incorporate it into the Ricardian framework and to generate testable hypotheses regarding its impacts on marginal effects of climate variables. Second, our approach enables us to measure directly the impact of crop insurance on the marginal effects of the climate variables whereas previous contributions use subsidies as just another control variable. In the latter case, the presence and magnitude of the subsidies affect the marginal effect of the climate variables indirectly only. Third, our contribution is also different from Annan and Schlenker (2015) because they rely on a crop production function. Theoretically, the Ricardian approach assumes that any adaptation strategy can take place as long as it can be capitalized in farmland value. Therefore, it provides a larger array of options for adaptation, such as land use change, compared to those subsumed in a crop production approach (Miao et al. 2016).

Another major difference with Annan and Schlenker (2015) is the choice of the variable measuring crop insurance. They work with the participation rate while this article casts the focus on the loss probability which, when measured over a long period, identifies the farmers' desire or lack thereof to adapt to new climate conditions more precisely. Indeed, the participation rate does not guarantee that farmers receive financial benefits from the crop insurance program. Annan and Schlenker (2015) discover that a higher crop insurance participation rate exacerbates the loss of corn and soybean yield caused by extreme degree-days[7]. Based on this evidence, they infer that crop insurance might discourage farmers from engaging in possible adaptation strategies, which, in turn, makes them more vulnerable to future extreme heat events. Given that the frequency and intensity of such events are expected to increase in the future according to the most recent IPCC report (IPCC 2014), this process will have detrimental consequences for the US agriculture.

In order to shed new lights into the role of crop insurance programs on the farmers' desire to adapt to new climate conditions, this article continues with a description of the proposed extension of the basic Ricardian framework. It shows that the response of land values to new climate conditions depends on the probability that losses actually happen. The following section lists the data sources, their summary statistics, and clarifies our model specification choices. In section 4, we present and discuss the estimation results while the last section summarizes the main findings and offers some concluding remarks.

2.2 Conceptual Framework

We start with the standard set-up of a Ricardian-type model and then extend it by introducing crop insurance programs. Finally, we illustrate the principles of the conceptual framework through three modified Ricardian graphs.

2.2.1 A formal theory of Ricardian analysis

As usual in the Ricardian literature, our starting point is the one of a representative farmer who chooses to allocate his land to the most lucrative use over a set of feasible alternatives. The long-run equilibrium agricultural profit experienced from exploiting land i is written as follows:

$$(2.1) \qquad \pi_i = \max_{j \in J} \{ p_j f_j [\mathbf{x}_{ij}(p_j, \mathbf{w}, c_i, \theta_i); c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij}(p_j, \mathbf{w}, c_i, \theta_i) + \varepsilon_{ij} \} - R_i$$

[7] Extreme degree-days are defined as the degree-days above certain heat thresholds that are harmful to crop growth. Annan and Schlenker (2015) set the thresholds based on values estimated empirically by Schlenker and Roberts (2009): 29ºC for corn and 30ºC for soybean.

Where j is the type of agricultural activity chosen among a set of locally doable J activities. The first term in the maximizing function is the revenue of operating activity j, i.e. the price of product j (p_j) times its output $f_j[\cdot]$. We denote the production function of activity j as a function of input $\mathbf{x}_{ij}$ and two groups of parameters, namely the climatic parameters c_i and the non-climatic parameters θ_i. The second term in the maximizing function corresponds to the cost incurred. It is calculated as the product of the input price vector $\mathbf{w}$ and of the vector of input use $\mathbf{x}_{ij}$. The farmer chooses inputs so as to maximize profits, hence the optimal input basket is driven by input and output prices as well as additional parameters in the production function: $\mathbf{x}_{ij}(p_j, \mathbf{w}, c_i, \theta_i) \equiv$ argmax $\{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij}\}$. The term ε_{ij} in the maximum parentheses is an additive zero-mean random error associated with the jth use of land. Its purpose is twofold. First, it captures the loss risk that is associated with any agricultural activity. Second, it can be viewed as a random error term as Schlenker et al. (2006) suggest. Last but not least, R_i is a fixed cost that corresponds to the land rent the farmer pays to the landlord. Last but not least, R_i is the rent farmers have to pay to the landlords.

In a long run equilibrium where farmers freely enter or leave the market, the expected profit should be zero. By setting $\mathbb{E}(\pi_{it}) = 0$, Eq. (2.1) implies that the rent is:

$$R_i = p_{j^*} f_{j^*}[\mathbf{x}_{ij^*}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij^*} \tag{2.2}$$

Where j^*denotes the optimal use of land i and where the arguments of the optimal input use function $\mathbf{x}_{ij^*}(\cdot)$ are suppressed for simplicity. Eq. (2.2) means that the long run land rent is equal to the net revenue obtained when the land is allocated to its optimal use.

Finally, since the Ricardian approach assumes that the farmland market is efficient, then land values V must equal the expected present value of future rents, that is:

$$(2.3) \qquad V_i = \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} R_i = \left(\frac{1+r}{r}\right) R_i = \left(\frac{1+r}{r}\right) \{p_{j^*} f_{j^*}[\mathbf{x}_{ij^*}; c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij^*}\}$$

Where r is the discount rate. Eq. (2.3) illustrates how farmland value reflects the long-run equilibrium relationship between local climate pattern and agricultural productivity. This result establishes the traditional rationale of the Ricardian analysis. However, the next section extends it to the presence of crop insurance programs that systematically dampen profit reduction due to poor harvest.

2.2.2 The role of crop insurance in the Ricardian framework

In essence, crop insurance is a policy that protects the farmers' revenue against production uncertainty. A typical insurance policy is comprised of two parameters: the (farmer-paid) premium rate[8], noted S, and the associated guaranteed revenue level M. At the beginning of the growing season, a farmer pays S to purchase the policy and, at the end of the season, if the net revenue realized is less than the guaranteed level M, the farmer will receive the difference through an indemnity payment. The long-run equilibrium agricultural profit with crop insurance is therefore:

$$(2.4) \qquad \pi_i = \max_{j \in J} \{\max\{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \varepsilon_{ij}, M_{ij}\} - S_{ij}\} - R_i$$

It is worth noting that, compared to Eq. (2.1), the realized net revenue attained from operating activity *j* with crop insurance is at least equal to the protected revenue M_{ij} minus the premium S_{ij}. In order to highlight this point, we should consider the net revenue for the optimal activity *j* with crop insurance:

$$\pi_{ij} = \begin{cases} p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij} - S_{ij} - R_i, & \text{with probability} \quad d_{ij} \\ M_{ij} - S_{ij} - R_i \qquad , & \text{with probability} \quad 1 - d_{ij} \end{cases}$$

[8] Currently, the average U.S. farmer benefits from the federal government subsidizing 70% of the premium. Therefore, a typical farmer pays the remaining 30% of the total premium. For clarity purposes, we suppress from equations (4)-(6) the notation of the subsidy ratio as it is irrelevant to our main conclusion as long as the subsidy ratio is independent of the climatic variables. This assumption can be easily confirmed since farmers planting the same crop are subject to the same subsidy ratio for their premium regardless of their physical location.

Where d_{ij} is the probability that the loss does *not* occur. The expected net revenue is therefore:

$$\mathbb{E}[\pi_{ij}] = \{p_j f_j[\mathbf{x}_{ij}, c_I, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij} - S_{ij}\} \cdot (d_{ij}) \tag{2.5}$$
$$+\{M_{ij} - S_{ij}\} \cdot (1 - d_{ij}) - R_i$$

The zero-profit assumption implies that the rent with a crop insurance program is:

$$R_i^{cp} = \{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij}\} \cdot (d_{ij}) + \{M_{ij}\} \cdot (1 - d_{ij}) - S_{ij} \tag{2.6}$$

The associated land value is:

$$V_i^{cp} = \left(\frac{1+r}{r}\right)\left\{\{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij}\} \cdot (d_{ij}) + \{M_{ij}\} \cdot (1 - d_{ij})\right\} - K_i \tag{2.7}$$

Where the constant K represents the impact of the farmer-paid premium on land value[9]. Taking the partial derivative of Eq. (2.7) with respect to the climate variable c_i, we calculate the marginal effect of climate on farmland value in the case of crop insurance as follows:

$$\frac{\partial V_i^{cp}}{\partial c_i} = (d_{ij}) \cdot \underbrace{\left\{\left(\frac{1+r}{r}\right)\frac{\partial}{\partial c_i}\{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij}\}\right\}}_{=\frac{\partial V_i}{\partial c_i}} < \frac{\partial V_i}{\partial c_i} \tag{2.8}$$

The term in braces is the marginal effect of climate without crop insurance. We can verify it by taking the derivatives of Eq. (2.3) with respect to c_i. The inequality in Eq. (2.8) holds because d_{ij} is a probability, therefore, it is less than one. This inequality relationship establishes our main conclusion in terms of how crop insurance affects the response of land value to changes in climate. Crop insurance makes land value less sensitive to changes in climate, which should not surprise

[9] This impact is relatively small in reality. If we focus on Illinois as an example, the farmer-paid premium is, on average, around 20 dollar per acre in 2018. Assuming a 10% discount rate, its total impact on the farmland value will be about 200 dollar per acre. Because Illinois' average farmland value is in the range of 5,000-10,000 dollars per acre, the premium paid by the farmer accounts for 1~2% of the total land value only. Note that it means the total premium would therefore represents 3.3~6.6% of the total land value, which is another reason not to model the 70% subsidy ratio explicitly.

us as the main purpose of introducing crop insurance is to reduce the volatility of farming revenue caused by natural causes.

Furthermore, Eq. (2.8) implies that the extent of this attenuation effect depends on $(1 - d_{ij})$, i.e. the probability that a loss occurs. The more likely is a farmer from suffering from a loss and receiving an indemnity, the less his land value responds to changes in climate. This theoretical insight motivates us to quantify the impact of the probability of a loss on the marginal effect of the climate variables on farmland value. This exercise will take place in section 3.

Before we move to it, it is important to discuss why we assume that the loss probability d_{ij}, the premium paid by the farmer S_{ij} and the revenue guarantee M_{ij} are orthogonal to the climate variables c_i in our conceptual model.

We believe that the loss probability is little correlated with the climate variables because climate is measured as the long-run average of the weather records (Mendelsohn and Massetti, 2017) and the probability that crop yield gets below a certain amount is linked to unexpected deviations from the mean rather than the mean itself. A similar argument holds for the premium paid by farmers. If it was set at its actuarially-fair level, the premium would be equal to the mean of the indemnity payment which is more likely to depend on the interannual variation of the weather variables than their 20- or 30-year averages.

When it comes to the revenue guarantee M, in many cases it is heavily affected by climate normal because the government sets it as the product of a chosen coverage rate and the average of a farmer's previous revenues. We can take this element into account by rewriting Eq. (2.8) as follows:

$$\text{(2.9)} \qquad \frac{\partial V_i^{cp}}{\partial c_i} = \left(d_{ij}\right) \cdot \frac{\partial V_i}{\partial c_i} + \left(1 - d_{ij}\right) \cdot \lambda \frac{\partial V_i}{\partial c_i} = \left(d_{ij} + \lambda - \lambda d_{ij}\right) \cdot \frac{\partial V_i}{\partial c_i} < \frac{\partial V_i}{\partial c_i}$$

where λ is the coverage rate which, by definition, is less than one. Our main conclusion remains, the marginal effects of climatic variables still suffer from a downward bias even though the magnitude of the bias reduces.

Before we move on to an illustrative example and actual econometric estimates, it is important to recall that the Ricardian framework is, in essence, a hedonic model. Rosen (1974)'s classic interpretation of the hedonic equilibrium allows us to further infer the disincentive effect of crop insurance on farmers' adaptation activities. Indeed, if the marginal effects of the climate variables are interpreted as the farmers' willingness to pay/accept for a favorable/unfavorable climate condition and if crop insurance allows to reduce the magnitude of these marginal effects, then insurance reduces the farmers' need for the most favorable climate conditions. A reduced need for the "optimal" climate means that farmers are less willing to adapt to more frequent and/or intense adverse climate conditions.

2.2.3 Illustrative example with two feasible activities

Figure 2.1 illustrates our conceptual framework. It is limited to two feasible activities for simplicity purposes. It is an extension of the figures found in Mendelsohn et al. (1994) and Deschênes and Greenstone (2007) where the expected net revenues are on the y-axis and temperature is on the x-axis. The net revenue curves for wheat and corn, the two activities we choose, represent how temperature affects the expected net revenues per acre due to planting each crop. Their quadratic shape and the capacity of the outer envelope to define the hedonic equilibrium are traditional in the literature and are explained in detail in the above references.

Panel (a) represents the well-known Ricardian mechanism by which a permanent increase in temperature from T_a to T_b would lead the farmer to switch his production from wheat to corn so that his revenue changes from A to B^{long}. While it appears as a drop compared to revenue A in our graphic example, it is equally likely that it represents a gain compared to A. What is certain, on the other hand, is that it is a better revenue outcome than B^{short} where the farmer has not adapted to new climate conditions. As a result, by switching crop, the farmer saved the revenue B^{long} - B^{short}.

Panel (b) assumes a similar climate change scenario but in the presence of crop insurance programs. The newly added vertical line represents the protected net revenue level of wheat production. As in panel (a), the farmer starts at *A*, a point where the expected net revenue of planting wheat is above the protected level. A warmer temperature causes the expected net revenue to drop below the protected level. Consequently, this wheat farmer would face an increasing probability of loss provided that his original insurance policy remains unchanged. In addition, the presence of crop insurance alters the Ricardian reasoning behind panel (a) in two profound ways. First, since crop insurance prevents the farmer's net revenue from dropping below the protected level, he no longer has a clear incentive to switch from wheat to corn under the warmer climate. Traditionally, this switch is the adaptation strategy the farmer is expected to take without crop insurance. Second, crop insurance reshapes the traditional outer envelope highlighted by a bold line that defines the hedonic equilibrium. This alteration corresponds to the diminished marginal effect of climate, as shown in equation (8).

2.3 Empirical Model

Estimating empirically whether crop insurance programs reduce the sensitivity of farmland values to local climate conditions is not trivial. A natural experiment would require comparing two identical farms with different loss probabilities. Identification would take place if the farmland value of the farm with the lower probability loss were to respond more strongly to changes in climate. Since farm-level data for the entire country is not available to the researchers, our identification strategy relies instead on the exogeneity of the loss probability measures across U.S. counties.

2.3.1 Data sources and processing issues

Our study is based on a panel dataset of farmland value, climate and soil quality variables measured over the 3,096 continental U.S. counties for the four most recent USDA censuses. We remove the urban counties from our sample because the possibility of converting farmland to urban development might largely inflate farmland values there (Plantinga et al. 2002). We follow Schlenker et al. (2006) in setting the urban county threshold at 400 inhabitants per square mile. As a result, our final sample is composed of 2,713 rural counties. We provide a detailed summary of the data sources and associated processing in table 2.1.

Our dependent variable is the (log of) average value of farmland and building per acre. Our independent variables can be classified into three categories: (1) the climate conditions; (2) population density and personal per capita income; and (3) nine soil quality control variables commonly used in the literature. Their description appears below.

Climate Normal --- Our climate data come from the North American Regional Reanalysis (NARR) dataset (Mesinger *et al*. 2006) of the National Center of Environmental Protection. The NARR dataset uses data assimilation methods to create a balanced panel of climate variables on a spatial grid from spatially unbalanced weather station observations. Data assimilation methods combine a physically-based climate model with actual weather station records to generate climate data where no weather station is present. They are more theory-based than the alternative approach called spatial extrapolation algorithms which achieves the same goal but merely relies on statistical techniques (Auffhammer *et al.* 2013). One example using the latter method is the commonly used Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset from Oregon

State University. While PRISM provides climate data on a monthly temporal resolution (Schlenker and Roberts 2009), NARR provides measurements every 3-hours and at a 32-km spatial resolution for the period 1979-2014. Following Schlenker et al. (2006), we decide to work with the growing season degree days and total precipitation to capture the climate normal in a county. All variables are averaged over a 20-year period (1992 - 2012). In addition, we include the squared value of each of them to capture their non-linear effects.

Drought Probability --- It is well-known that climate change is accompanied by an increase in the frequency and intensity of extreme weather events (IPCC 2014). Among them, drought is arguably the most relevant natural disaster to agriculture. To investigate its impact on farmland value, we define the probability of a drought based on the Palmer Drought Severity Index (PDSI). PDSI measures the standard deviation of a given month's rainfall from its historical average. Its value usually ranges from +10 to -10 whereby a negative PDSI roughly means the current precipitation is less than its historical average and corresponds to a drought. We count a month as a drought month if its monthly PDSI is less than -3, which corresponds to a drought that is between severe and extreme. Then, we count the number of times a county is under such drought over our 20-year period and call this ratio the probability of a drought.

Crop Insurance --- The crop insurance data come from the Summary of Business (SOB) of USDA's Risk Management Agency (RMA). SOB includes county-level actuarial performance for different crop insurance policies over 1980-2015. Two policies are considered to be different by SOB if they have differences in any of the following features: insured crop, insurance plan, coverage level. For each policy, the raw data contains the information such as the total number of contracts, total premium, government subsidy, indemnity payments and loss ratios. Since there are always more than one policy sold in a county, we have to aggregate the raw data by agricultural activity types, insurance plan and coverage category to county averages of premium, subsidy and indemnity using total liability of each categories as the weights.

Socioeconomic Characteristics --- The data capturing human intervention come from several sources. Population density is from the U.S. Census Bureau while personal income per capita comes from the U.S. Bureau of Economic Analysis. These two variables serve as proxies for the level of demand of agricultural goods and of urban development upon farmland. They are widely used in the Ricardian literature. All our monetary variables are converted to 2012 dollar using the PPI index for farm products from the U.S. Bureau of Labor Statistics. The only exception is personal income for which we use the GDP deflator from the U.S. Bureau of Economic Analysis.

Soil Quality --- We control for spatial differences in soil quality and topographic characteristics by relying on USDA's General Soil Map National Resource Inventory (STATASGO2). These data capture the flood frequency ratio, erosion factor, slope steepness, wetland ratio, electrical conductivity ratio, available water capacity ratio, clay content, sand content, longitude, latitude and elevation.

2.3.2 Measures for the loss probability

Approximating the probability of a loss claim to be made is an empirical challenge. If we could observe the individual farms' loss history, then the frequency of the indemnity being non-zero over a long time period would be the unbiased estimator of such probability. Unfortunately, due to privacy protection concerns, only county-level actuarial records are accessible to the public. The probability of having a positive indemnity at the county level is much larger than the probability at the single farm level, as the county's total indemnity is zero only when not a single farm in that county makes a loss claim, which is highly impossible.[10] Therefore, the frequency of the positive indemnity measured at the county level heavily overestimates the farm-level loss probability. In this manuscript, we propose two alternative methods to approximate the loss probability discussed in the theoretical model.

The first approach still relies on the county-level loss performance but adjusts it by setting a higher level for a year to be classified as a loss year. This threshold should approximate the indemnity payment in the county during the normal years and it is only when a year's indemnity exceeds that threshold that we can count it as a loss year. There are two obvious candidates for such threshold: total premium and farmer-paid premium. When total premium is used as a threshold, we simply approximate the loss probability as the frequency of having larger than one loss ratio. Recall the loss ratio is the ratio of indemnity to total premium. Another option is to use the farmer-paid premium, which is usually 30% of the total premium for most U.S. farmers. Unsurprisingly, this choice of threshold usually leads to higher estimates of loss probability than the previous one.

The second method approximates the loss probability by the probability of a crop failure. One measure of the latter commonly suggested in the literature (Irwin and Good, 2012) is the probability of the current yield to be below its time trend. Agricultural economists (Irwin and Good, 2014; Good et al., 2016) have a long tradition to regress crop yield on time in order to produce the benchmark trend yield over a given period. If the current yield drops below a certain percentage of the trend yield, then it corresponds to a crop failure. Here, we select the main crop produced in each county, fit a linear time trend model using the period from 1972 to 2017, count

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[10] This argument is easy to verify using a numerical example. Consider there are ten farms in a county. Each of them has 0.1 probability to have positive indemnity. Then, the probability for the whole county to have positive indemnity will be ($1- (0.9)^{10} = 0.65$) which is far greater than 0.1.

the number of years the yield falls below 80% of the trend yield and define the loss probability accordingly. Compared to the first method, this approximation is more likely to be seen as clearly exogenous as the calculation of this probability is under no influence of any economic agent. For instance, it does not require the premium rate set by USDA's risk management agency.

2.3.3 Summary statistics

Table 2.2 reports the mean value of the main variables measured over the sample of 2,713 rural counties for 1997, 2002, 2007 and 2012. Panel A shows the cropland-weighted mean of the time-variant economic variables. During the study period, land value increases by roughly 175%, from $ 1,186 in the 1997 to $ 3,254 in 2012. The growth rate of land value accelerated significantly between the last two agricultural census years due to the bioenergy boom. On the other hand, the population density declined by around 1%, as one would expect from increasing urbanization over this period (Ortiz-Bobea 2016). Meanwhile, the per capita income too increased from 1997 to 2012. Panel B details the variables associated with crop insurance programs, namely the participation rate and three measures of loss probabilities. Thanks to the increasingly generous premium subsidy from the federal government (Shields 2013), the average participation rate almost doubled during the study period. On the other hand, the three loss probability measures remained unchanged across years because they are defined as the frequency of loss events over the entire period. Finally, panel C lists the locational attributes such as the long-run climate variables and the soil characteristics. While the raw data of these variables are essentially time-invariant, the small variation measured across the years actually comes from changes in the cropland acreage which is used as weight in the calculation of the average. For example, the drop from 502 mm to 497 mm in long-run average growing season precipitation comes exclusively from the fact that croplands expanded mostly in the drier regions of the country over the study period.

Figure 2.2 offers a closer look at the empirical distribution of the loss probability, our variable of interest. Panel A illustrates the empirical density plot of each of the three definitions offered above, while panel B shows their respective box plots. The first candidate, named "rma_total" (red curve), approximates the loss probability calculated by the frequency of the indemnity surpassing the total premium. The second choice, named "rma_farm" (green curve), is based on the same approach but uses farmer-paid premium instead of total premium. The last alternative, named "crop_failure" (blue curve), is based on the frequency of the crop yield to be beneath 80% of its linear time trend yield.

Several interesting observations emerge from comparing these loss probability measures with each other. First, the "rma_farm" approach displays both the highest mean and variance among all three alternatives. The "rma_total" approach, on the other hand, produces more conservative estimates for the loss probability. The median is less than 30%, and the third quartile is less than 50%. The change is predictable given the fact that the threshold for identifying a loss event with "rma_total" is almost three times as large because average premium subsidy rate is around 30%. Third, the loss probability measured by the "crop_failure" approach displays the lowest mean and standard deviation. With the exception of a few outliers, the large majority of the probability distribution lies below 50%. This phenomenon can be explained by the fact that this measure is based on exogenous productivity shocks and has a very limited chance to be influenced by any man-made mispricing of crop insurance policies.

2.3.4 Model specification choices

Our model builds on the standard Ricardian regression models and can be formulated as follows:

$$\mathrm{y}_{\mathrm{ijt}} = \overline{\mathbf{T}}_{\mathrm{ij}}'\boldsymbol{\delta}_1 + \overline{\mathbf{T}}_{\mathrm{ij}}^{2\prime}\boldsymbol{\delta}_2 + \left(\overline{\mathbf{T}}_{\mathrm{ij}}' \times \mathrm{L}_{\mathrm{ij}}\right)\boldsymbol{\gamma}_1 + \left(\overline{\mathbf{T}}_{\mathrm{ij}}^{2\prime} \times \mathrm{L}_{\mathrm{ij}}\right)\boldsymbol{\gamma}_2 + \mathbf{X}_{\mathrm{ijt}}'\boldsymbol{\beta} + \mathbf{Z}_{\mathrm{ij}}'\boldsymbol{\alpha} + \xi_{\mathrm{jt}} + \epsilon_{\mathrm{ijt}} \qquad \text{where } \epsilon_{\mathrm{ijt}} \sim \mathrm{N}(0, \sigma_\epsilon^2) \tag{2.10}$$

Where subscript i is the county index, j is the state index and t represents time. **T** stands for the matrix of variables describing climate normal. We also add the square terms of temperature and precipitation, represented by $\mathbf{T}^2$, to capture their nonlinear effect (Mendelsohn and Massetti 2017). **X** is a matrix of time-variant socioeconomic controls while **Z** captures all the time-invariant soil quality variables.

Our model introduces heterogenous marginal effects through the loss probability L so that the coefficients $\boldsymbol{\gamma}$ capture the difference in the marginal effects of **T** on farmland value among counties with a high loss probability. Furthermore, $\boldsymbol{\gamma}$ significantly greater than $\boldsymbol{\delta}$ would indicate that counties with higher loss probability are less sensitive to changes in climate conditions than low loss probability counties and would support our hypothesis that crop insurance programs dampen adaptation to climate change. Last but not least, we add the year-by-state fixed effects ξ_{jt} to control for the unobservable factors that might confound the marginal effect of climate (Schlenker et al., 2006; Deschênes and Greenstone, 2007). Specifically, they capture time trends that are common to the counties of the same state and which might be generated by changes in commodity prices, technological innovations, business cycles and state-level policy shocks.

Finally, previous Ricardian contributions, namely Schlenker et al. (2006), Deschênes and Greenstone (2007), Dall'erba and Dominguez (2015), have highlighted that the error term of Eq. (2.7) might suffer from heteroscedasticity, serial autocorrelation and/or spatial dependence given the irregularities in the size and shape of the counties and given the similarities in soil, climate and socio-economic conditions across nearby places. Moran's I test and Breusch-Pagan test confirm these hypotheses at the 5% level. Therefore, the spatial heteroskedasticity and autocorrelation consistent (spatial HAC) estimator developed by Conley (2008) is used to estimate the consistent standard error for statistical inference.[11]

2.4 Results

We start with reporting the results for the baseline regression. In Section 4.2, we extend the baseline regression to incorporate the impact of the participation rate.

2.4.1 Baseline regression results

We use Eq. (2.10) as the main model specification of this article and its estimation results are reported in table 2.3. Soil quality controls, socioeconomic conditions and the state-by-year fixed effects are included as regressors in all regressions, but their marginal effect is not reported for clarity purposes[12].

The first column of table 2.3 reports the marginal effects of the climate variables in the standard Ricardian model, i.e. the model without interaction terms using all counties in our sample. Two results are inconsistent with our expectations. First, growing degree day (GDD) has a negative and non-significant effect. It contradicts the findings of both the Ricardian literature (Schlenker et al. 2006; Fezzi and Bateman 2015) and common agronomy knowledge (Miller et al. 2001, Schlenker and Roberts 2009) which predicts that GDD has a significant positive impact on yield, hence affects farmland value in the same direction. Second, the probability of a drought is found to affect farmland value positively, which is obviously a counter-intuitive statement.

Such unexpected estimates might be caused by mistakenly pooling dryland and irrigation counties in a single regression equation, which was first pointed out by Schlenker et al. (2005).

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[11] Robust standard errors a la Conley takes the following sandwich form: $X'\hat{\Sigma}X = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j' e_i e_j K(d_{ij}/d)$ where $K(\cdot)$ is the kernel function (we use Epanechnikov), d_{ij} is the distance between two counties' centroids and d is the bandwidth of the kernel (we use 250 km as Moran's I suggests a significant decay in spatial autocorrelation of the residuals beyond this distance).

[12] Complete results available from the authors upon request.

Restricting the sample to the dryland counties only is one solution (Schlenker et al., 2005) and the eastern side of 100° meridian has often been used in that purpose (Schlenker et al., 2006; Burke and Emerick 2015). As a result, we run our model again but on a sample restricted to the 2,178 eastern U.S. counties. Estimations results are displayed in column (2). The marginal effects of both GDD and precipitation display the expected sign and concave return on farmland value now. In addition, the model fit has improved from 0.796 to 0.832 in terms of adjusted R^2. This better fit is further confirmed by a LR test with p-value = 0.000. However, the positive effect of the probability of a drought remains puzzling, even though its magnitude has diminished compared to the full sample case (column 1).

The last two columns display the coefficient estimates of our extended Ricardian model, Eq. (2.10) on the sample of dryland counties. Column (3) is associated with the specification where the loss probability is based on the number of times the insurance indemnity is greater than the farmer-paid premium. First, the Chow-Wald test result (p-value = 0.000) confirms that including the loss probability leads to significantly modifying the marginal effect of our covariates. In particular, we note that an increase in the loss probability significantly decreases the marginal effect of GDD on farmland value. For instance, a 10% increase in loss probability will lead to a 0.2 point decrease in the marginal effect of GDD. While crop insurance clearly distorts the marginal effect of GDD on farmland value, its impact on precipitation indicates an amplification rather than a reduction of its marginal impact on land value. One plausible explanation is that dryland counties have experienced drier conditions over time which have led to an increasing loss probability. Another reason could be that the moral hazard that crop insurance creates precludes its participants from investing in the development of their irrigation system.

The marginal effects reported in column (4) are our preferred estimates because, as argued above, when the loss probability is measured by the frequency of current yield being below its trend value, it relies on exogenous productivity shocks only. In other words, the coefficient estimates in this column are more likely to be unbiased and consistent because the exogeneity of this variable is more straightforward. In addition, our results confirm the existence of heterogeneous marginal effects of the climate variables (Chow-Wald test has a p-value = 0.000). An increase in the loss probability now switches the marginal effect of GDD from positive to negative and magnifies the return on precipitation even further than in specification (3). In addition, the new estimates offer a plausible explanation to the puzzling positive impact of drought probability found in specifications (1) and (2). Without the distortion of crop insurance, the marginal effect of the probability of a drought is negative and significant, as one would expect. However, when the probability of relying on crop insurance increases, the marginal effect of drought switches sign and offers a clear evidence of the lack of incentive for adapting to drought events. For instance, in spite of the severity of the 2012 drought experienced in most of the Midwest, many farmers earned record-breaking revenue that year.

2.4.2 The participation effect

In this section, we test the robustness of our conclusion to incorporate the participation rate of crop insurance. Annan and Schlenker (2015) use the participation rate as the program intensity measure to assess the reduction in adaptation to extreme heat in corn and soybean production. We, on the other hand, try to incorporate this variable into our extended Ricardian framework.

Conceptually, we anticipate that a higher participation rate leads to a higher distortion of the marginal effect of the climate variables on land value. Consider the case in which there is a representative farmer in the county. A low participation rate in the county is equivalent to the representative farmer purchasing crop insurance for a small proportion of his land only and leaving the majority of his land out of the program. No matter how severe the distortion of the marginal effect in that small portion of land might be, its impact will be diluted by the marginal effect in the majority of land which, itself, is not affected by the program at all. To test this hypothesis, we extend the baseline regression equation by adding a term interacting the climate variable (**T**), the loss probability (L) and the participation rate (P) as seen in Eq. (2.11). A confirmation of our hypothesis would require this triple interaction term ($\boldsymbol{\tau}$) to share the same sign as the interaction term ($\boldsymbol{\gamma}$) but to be greater in absolute value.

$$\begin{aligned}\mathbf{y_{ijt}} &= \mathbf{\bar{T}_{ij}'\delta_1 + \bar{T}_{ij}^{2\,\prime}\delta_2 + \left(\bar{T}_{ij}' \times L_{ij}\right)\gamma_1 + \left(\bar{T}_{ij}^{2\,\prime} \times L_{ij}\right)\gamma_2} \\ &\quad \mathbf{+\left(\bar{T}_{ij}' \times L_{ij} \times P_{ij}\right)\tau_1 + \left(\bar{T}_{ij}^{2\,\prime} \times L_{ij} \times P_{ij}\right)\tau_2} \\ &\quad \mathbf{+ X_{ijt} + Z_{ij}\alpha + \xi_{jt} + \epsilon_{ijt}} \qquad \textbf{where } \mathbf{\epsilon_{ijt} \sim N(0, \sigma_\epsilon^2)}\end{aligned} \tag{2.11}$$

Table 2.4 reports the regression results of Eq. (2.11). The first column displays the $\boldsymbol{\delta}$ coefficients that capture the direct marginal effect of the climate variables. The second column displays the $\boldsymbol{\gamma}$ coefficients where, like in table 2.3, the loss probability is interacted with the climate variables. Finally, the triple interaction term is present in the third column. This specification not only confirms our main results but it also enriches further our conclusions. Take the first row, GDD, as an example. While the switch in sign confirms the results of table 2.3, the negative sign in column three indicates that the distortion of the crop insurance program on the marginal effect of GDD significantly increases with participation in the program. When it comes to the marginal effect of the probability of a drought, the non-significant result in column (3) indicates that it is not different from the one in column (2). As a result, the participation rate does not modify the extent to which crop insurance reduces adaptation to drought.

Despite being ignored by Annan and Schlenker (2015), the potential endogeneity of the participation rate has been discussed by many authors including Smith and Goodwin (1996), Wu

(1999) and Deryugina and Konar (2017). Therefore, we replicate in panel B the above analysis using a high participation rate dummy to replace the participation rate itself. We give this dummy the value one when a county belongs to one of following three farm production regions: the corn belt, the northern plains and the lake states. This dummy is clearly exogenous as it is defined based on pre-determined geographical boundaries; yet, as figure 2.3 illustrates, the participation rates in those three regions are significantly higher (mean = 0.69, min = 0.53 , max = 0.72) than the rest of the country (mean = 0.36, min = 0.2, max = 0.43). All our results confirm our expectations and panel A's findings.

2.5 Conclusion

In spite of its increasing popularity (Mendelsohn and Massetti 2017), the Ricardian model has never considered whether the government-supported assistance programs to farmers constitute a moral hazard that reduce their need to adapt to new climate conditions. This paper takes the first step in this direction and demonstrates that federal crop insurance programs reduce significantly or even cancel out the farmers' willingness to adapt. We start by extending the traditional Ricardian setting to reflect that profit-maximizing farmers take their production decisions based on the certainty that paying an insurance premium guarantees they will receive support benefits in the case of a bad harvest. Results indicate that the crop insurance programs can heavily distort the farmers' incentive to adapt to new local climate conditions whether they represent continuous events, such as degree days, or more extreme events such as the probability of a drought.

The climate adaptation reduction effect induced by current crop insurance programs might cause a considerable deadweight loss in the long run. Indeed, not only do crop insurance participants receive some federal support to help them finance a part of their annual premium payment, but the government subsidizes also the net recipients through indemnity payments.

Ultimately, if the policy makers aim at minimizing the potential damage of climate change on the U.S. agriculture, new crop insurance programs should be defined to function as a social safety net in the short run only. In the long run, a more efficient policy would consist in helping the vulnerable farmers adopt new technologies, consider other crops and absorb more often the costs associated to bad planting decisions (Antel and Capalbo 2010; Kandlikar and Risbey 2000; Smit and Skinner, 2002; Mendelsohn 2006; Howden et al. 2007; Zilberman et al. 2012; Hertel and Lobell 2014).

Figures and Tables:

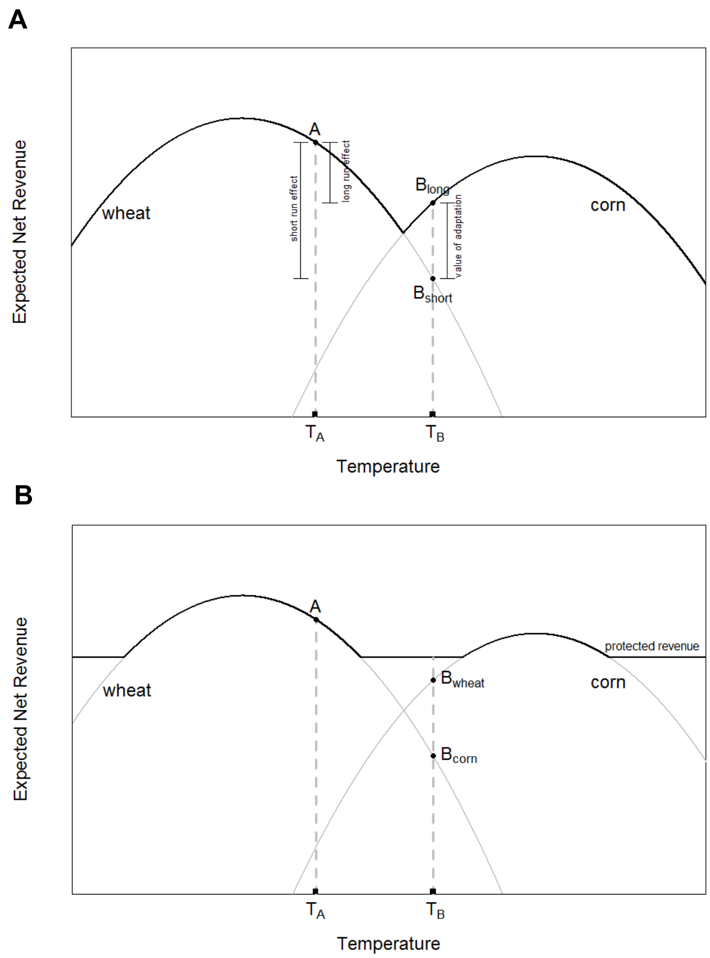


FIGURE 2.1 AN ILLUSTRATIVE EXAMPLE FOR THE THEORETICAL FRAMEWORK

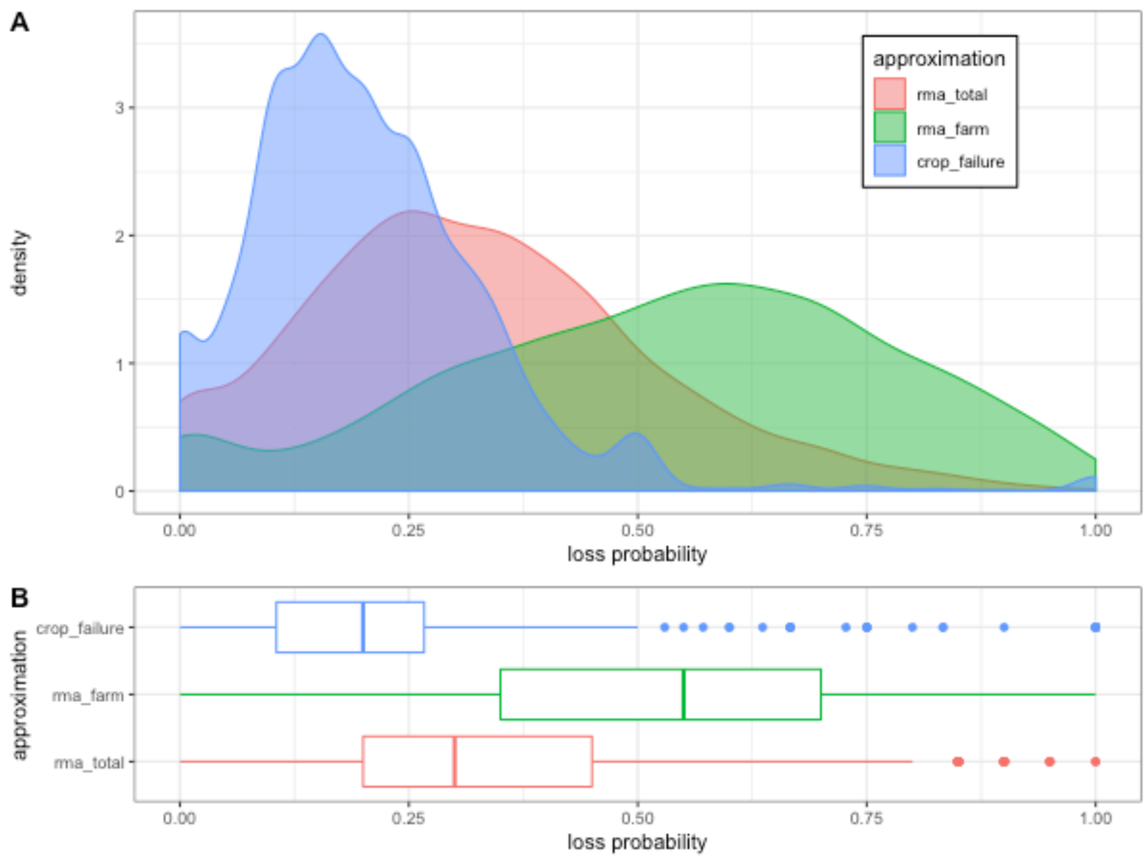


FIGURE 2.2 DENSITY PLOTS OF LOSS PROBABILITY

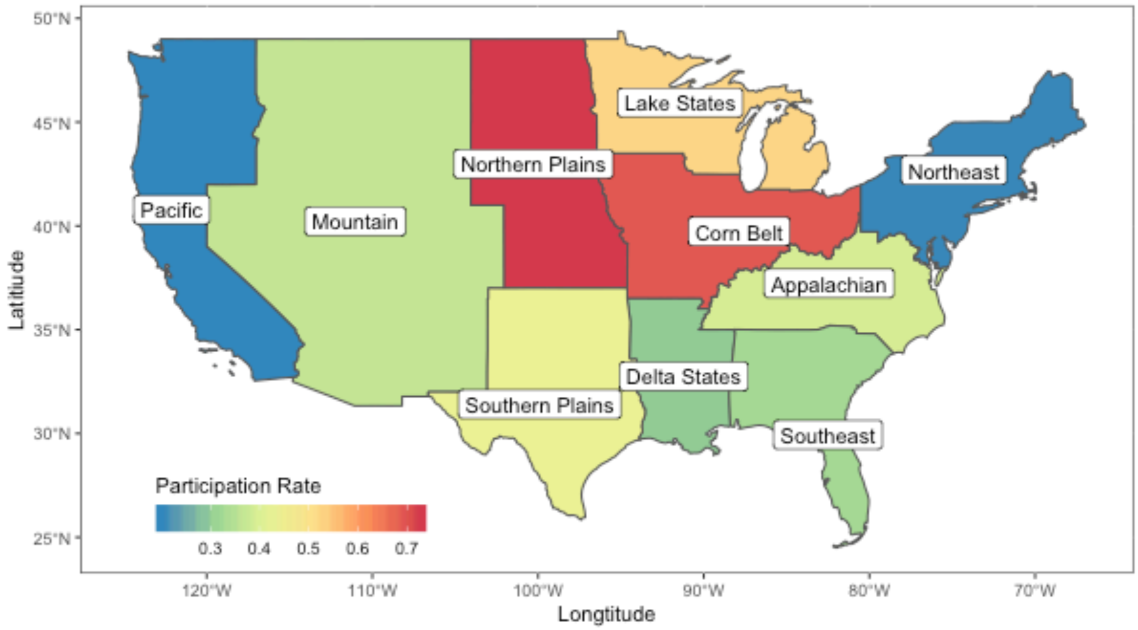


FIGURE 2.3 RATES OF PARTICIPATION IN CROP INSURANCE ACROSS FARM PRODUCTION REGIONS

TABLE 2.1 DATA DESCRIPTIONS AND SOURCES

Variable	Explanation	Unit	Sources
Land value	Value of land & buildings per acre	$/acre	(1)
Farmland	The acreage of farmland within a county	acre	(1)
Cropland	The acreage of cropland within a county	acre	(1)
Corn yield	Corn yield for each county since 1972	bu/acre	(1)
Wheat yield	Winter wheat yield for each county since 1972	bu/acre	(1)
Cotton yield	Upland cotton yield for each county since 1972	bu/acre	(1)
Soybean yield	Soybean yield for each county since 1972	bu/acre	(1)
Crop sales	The monetary amount received by farmers from selling crops	$	(1)
Population density	Population density per square miles	person/mile2	(2)
Personal income	Per capita personal income	$/person	(3)
Flood Frequency	Flooding is the temporary inundation of an area caused by overflowing streams, by runoff from adjacent slopes, or by tides.	0 ~ 0.1	(4)
K factor ratio	Erosion factor K indicates the susceptibility of a soil to sheet and rill erosion by water.	0.02 ~ 0.69	(4)
Slope steepness	Slope gradient is the difference in elevation between two points, expressed as a percentage of the distance between those points	%	(4)
Wetland ratio	Fraction of the land occupied by wetland (This rating indicates the proportion of map units that meets the criteria for hydric soils)	0 ~ 0.1	(4)
Salinity	Electrical conductivity (EC) is the electrolytic conductivity of an extract from saturated soil paste, expressed as millimhos per centimeter at 25 degrees C. Electrical conductivity is a measure of the concentration of water-soluble salts in soils. It is used to indicate saline soils.	mmhos/cm	(4)
Permeability	Saturated hydraulic conductivity (Ksat) refers to the ease with which pores in a saturated soil transmit water.	um/s	(4)
Moisture Capacity	Available water capacity (AWC) refers to the quantity of water that the soil is capable of storing for use by plants.	cm/cm	(4)
Clay content	Clay as a soil separate consists of mineral soil particles that are less than 0.002 millimeter in diameter.	%	(4)
Sand content	Sand as a soil separate consists of mineral soil particles that are 0.05 millimeter to 2 millimeters in diameter.	%	(4)
Elevation	The elevation of a geographic location is its height above or below a fixed reference point, most commonly a reference geoid	m	(4)
Growing degree-days	Cumulative growing degree days over the entire growing season (Apr.1st to Sep. 30th)	°C/day	(5)
Precipitation	Total precipitation over the entire growing season (Apr.1st to Sep. 30th)	mm	(5)
PDSI	Monthly Palmer Drought Severity Index (raster)	-6 ~ +6	(5)
Drought probability	The frequency of drought events over 20-year period	0 ~ 1	(S)
Total premium	Total premium collected for crop insurance	$	(6)
Farm-paid premium	The amount of premium paid by the farmers	$	(6)
Total Indemnity	Total indemnity paid to the farmers	$	(6)
Participation rate	The ratio of total liability to the crop sales	%	(S)
LP_ RMA_total	Loss possibility measured based on the frequency of the events when total indemnity is greater than total premium.	%	(S)
LP_ RMA_farm	Loss possibility measured based on the frequency of the events when total indemnity is greater than farm-paid premium.	%	(S)
LP_crop_failure	Loss possibility measured based on the frequency of the events when crop yield is below 80% of its time trend yield	$	(S)

Notes: (1) USDA NASS Quick Stats; (2) USCB Population and Housing Unit Estimates; (3) BEA Regional Economic Accounts; (4) U.S. Geological Survey; (5) North American Regional Reanalysis; (6) USDA RMA Summary of Business; and (S) self-calculated based on public-accessible datasets.

TABLE 2.2 COUNTY-LEVEL MEAN VALUES BY YEAR

	1997	2002	2007	2012
FARMLAND AND ITS VALUE				
Land value per acres of land in farm ($/acre)	1,186.16	1,461.59	2,239.14	3,254.29
SOCIOECONOMIC VARIABLES				
Population Density per sq. mile (person/mile^2)	51.39	51.77	50.94	50.98
Personal Income per capita ($/person)	20,811.53	24,682.89	32,240.36	41,040.65
LOSS PROBABILITIES				
Participation rate (%)	0.34	0.48	0.53	0.60
Loss prob. (indemnity > total premium)	0.32	0.32	0.31	0.31
Loss prob. (indemnity > farmer-paid premium)	0.56	0.56	0.56	0.56
Loss prob. (yield < 0.8 × trend yield)	0.19	0.19	0.19	0.19
CLIMATE AND WEATHER VARIABLES				
Total precipitation (mm)	502.76	500.74	497.78	497.51
Growing degree-day (Celsius °C)	2,129.59	2,121.44	2,097.21	2,085.92
Drought probability (%)	0.06	0.06	0.06	0.06
MEASURES OF SOIL QUALITIES				
Slope steepness (%)	8.01	8.00	7.68	7.47
Flood Frequency ratio (%)	0.07	0.07	0.07	0.07
Erosion Factor (0.01 inch)	0.29	0.29	0.29	0.29
Permeability (cm/s).	16.32	16.25	16.14	16.01
Moisture Capacity (cm/cm)	0.17	0.17	0.17	0.17
Salinity (mmhos/cm)	0.24	0.24	0.24	0.24

TABLE 2.3 ESTIMATES OF THE IMPACT OF LOSS PROBABILITY ON FARMLAND VALUE

Specification	(1)	(2)	(3)	(4)
	Benchmark_all	Benchmark_east	RMA_farm_east	Crop_failure_east
Growing degree-day	-0.076	1.527***	2.585***	2.683***
	(0.212)	(0.200)	(0.325)	(0.315)
Growing degree-day^2	-0.091*	-0.541***	-0.748***	-0.773***
	(0.051)	(0.045)	(0.073)	(0.072)
Total precipitation	0.358***	0.537***	0.138	0.300**
	(0.070)	(0.093)	(0.132)	(0.135)
Total precipitation^2	-0.022***	-0.036***	-0.008	-0.018*
	(0.005)	(0.007)	(0.010)	(0.010)
Drought probability	0.825***	0.756***	0.200	-0.876*
	(0.310)	(0.258)	(0.557)	(0.449)
Growing degree-day ×Loss prob.			-2.040***	-5.071***
			(0.492)	(1.038)
Growing degree-day ^{2}×Loss prob.			0.451***	1.118***
			(0.107)	(0.228)
Total precipitation×Loss prob.			0.540***	1.387***
			(0.163)	(0.352)
Total precipitation^2×Loss prob.			-0.039***	-0.107***
			(0.012)	(0.027)
Drought probability×Loss prob.			0.892	9.083***
			(0.892)	(2.056)
Socioecon. variables	Yes	Yes	Yes	Yes
Soil variables	Yes	Yes	Yes	Yes
State×year fixed effects	Yes	Yes	Yes	Yes
Observations	10,656	8,712	8,432	7,756
Adj. R-squared	0.796	0.832	0.843	0.844
Chow-Wald test (F-test)			10.77***	14.43***

Note: in each column, the dependent variable is farmland value per acre at four agriculture census years: 1997, 2002, 2007 and 2012. Standard errors are in parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors à la Conley (2008) control for heteroskedasticity and spatial dependence.

TABLE 2.4 ESTIMATES OF THE IMPACT OF PARTICIPATION ON FARMLAND VALUE

Specification	PANEL A: CONTINUOUS EFFECT			PANEL B: DUMMY VARIABLE EFFECT		
	Climate	Climate ×Loss Prob.	Climate ×Loss prob. ×participation rate	Climate	Climate ×Loss Prob.	Climate ×Loss prob. ×participation rate
Growing degree-day	2.662***	-2.840**	-5.646***	2.560***	-2.492**	-7.415***
	(0.329)	(1.113)	(1.174)	(0.312)	(1.185)	(1.583)
Growing degree-day ^{2}	-0.761***	0.683***	1.057***	-0.744***	0.523**	1.775***
	(0.0755)	(0.245)	(0.247)	(0.073)	(0.261)	(0.399)
Total precipitation	0.245*	0.577	2.203***	0.332**	0.725*	2.335***
	(0.133)	(0.385)	(0.461)	(0.136)	(0.399)	(0.534)
Total precipitation^2	-0.014	-0.042	-0.183***	-0.020*	-0.056*	-0.199***
	(0.010)	(0.030)	(0.038)	(0.010)	(0.031)	(0.045)
Drought probability	-0.928**	7.994***	3.564	-0.407	4.641**	3.266
	(0.459)	(2.355)	(2.700)	(0.501)	(2.236)	(2.748)
Socioecon. variables		Yes			Yes	
Soil variables		Yes			Yes	
State×year fixed effects		Yes			Yes	
Observations		7,351			7,756	
Adj. R-squared		0.853			0.846	
Chow-Wald test (F-test)		17.50***			14.33***	

Note: in each column, the dependent variable is farmland value per acre at four agriculture census years: 1997, 2002, 2007 and 2012. Standard errors are in parentheses and * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors à la Conley (2008) control for heteroskedasticity and spatial dependence.

References:

Antle, J. M., and S. M. Capalbo. 2010. "Adaptation of agricultural and food systems to climate change: an economic and policy perspective." *Applied Economic Perspectives and Policy* 32(3): 386-416.

Annan, F., and W. Schlenker. 2015. "Federal crop insurance and the disincentive to adapt to extreme heat." *The American Economic Review - Papers and Proceedings* 105(5): 262-266.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel. 2013. "Using weather data and climate model output in economic analyses of climate change." *Review of Environmental Economics and Policy* 7(2) 181-198.

Burke, M., and K. Emerick. 2016. "Adaptation to climate change: Evidence from US agriculture." *The American Economic Journal: Economic Policy* 8(3): 106-140.

Coble, K. H., and T. O. Knight. 2002. "Crop insurance as a tool for price and yield risk management." In J., Richard E., Pope, R. D. ed. *A Comprehensive Assessment of the Role of Risk in US Agriculture*, Springer US, pp. 445-468.

Conley, T. G. 2008. "Spatial Econometrics", in S. N. Durlauf and L. E.Blume, ed. *The New Palgrave Dictionary of Economics*, Vol. 7, Second Edition, Houndsmills: Palgrave Macmillan. pp. 741-747.

Dall'erba, S., and F. Domínguez. 2016. "The Impact of Climate Change on Agriculture in the Southwestern United States: The Ricardian Approach Revisited." *Spatial Economic Analysis* 11(1):46-66.

Deryugina, T., and M. Konar. 2017. "Impacts of crop insurance on water withdrawals for irrigation." *Advances in Water Resources*.

Deschenes, O., and M. Greenstone. 2007. "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather." *The American Economic Review* 97(1):354-385.

Environmental Working Group. "USDA Subsidies for farms in The United States totaled $322.7 billion in subsidies from 1995 through 2014", Accessed on April. 16th 2017. https://farm.ewg.org/regionsummary.php?fips=00000&regionname= theUnitedStates.

Good, D., T. Hubbs and S. Irwin. 2016 "Assessing South American Corn Yield Risks: Estimating the Yield Trend." *farmdoc daily* (6):212, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Goodwin, B. K., and V. H. Smith. 1995. *The economics of crop insurance and disaster aid.* Washington DC: American Enterprise Institute.

Hertel, T. W., and D. B. Lobell. 2014. "Agricultural adaptation to climate change in rich and poor countries: Current modeling practice and potential for empirical contributions." *Energy Economics* 46(4):562-575.

Howden, S. Mark, Jean-François Soussana, Francesco N. Tubiello, Netra Chhetri, Michael Dunlop, and Holger Meinke. 2007. "Adapting agriculture to climate change." *Proceedings of the national academy of sciences* 104(50):19691-19696.

IPCC. 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer, ed.]. IPCC, Geneva, Switzerland.

Irwin, S. and D. Good. 2012. "Recent Observations on the Tolerance of Corn Yield to Drought Conditions." *farmdoc daily* (2):107, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Irwin, S. and D. Good. 2014. "The 2014 U.S. Average Corn Yield: Big or Really Big?." *farmdoc daily* (4):127, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

Kandlikar, M., and James R.. 2000. "Agricultural impacts of climate change: if adaptation is the answer, what is the question?" *Climatic change* 45(4): 529-539.

Knight, T.O., and K. H. Coble. 1997. "Survey of US multiple peril crop insurance literature since 1980." *Review of Agricultural Economics* 19(1):128-156.

Massetti, E., and R. Mendelsohn. 2011. "Estimating Ricardian models with panel data." *Climate Change Economics* 2(4):301-319.

Mendelsohn, R., and A. Dinar. 2003. "Climate, water, and agriculture." *Land Economics* 79(3):328-341.

Mendelsohn, R., W. D. Nordhaus, and D. Shaw. 1994. "The impact of global warming on agriculture: a Ricardian analysis." *The American Economic Review* 84(4):753-771.

Mendelsohn, R. O., & Massetti, E. (2017). The use of cross-sectional analysis to measure climate impacts on agriculture: theory and evidence. *Review of Environmental Economics and Policy*, 11(2), 280-298.

Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell, P. C. Shafran, W. Ebisuzaki, D. Jović et al. 2006. "North American regional reanalysis." *Bulletin of the American Meteorological Society* 87(3):343-360.

Miao, R., M. Khanna, and H. Huang. 2015. "Responsiveness of crop yield and acreage to prices and climate." *American Journal of Agricultural Economics* 98(1):191-211.

Miller, P., Lanier, W., & Brandt, S. 2001. "Using growing degree days to predict plant stages". Ag/Extension Communications Coordinator, Communications Services, Montana State University-Bozeman, Bozeman, MO, 1-2.

Ortiz-Bobea, A. 2016. "The economic impacts of climate change on agriculture: accounting for time-invariant unobservables in the hedonic approach", working paper (No. 642-2016-44322).

Plantinga, A. J., R. N. Lubowski, and R. N. Stavins. 2002. "The effects of potential land development on agricultural land prices." *Journal of Urban Economics* 52(3):561-581.

Polsky, C. 2004. "Putting space and time in Ricardian climate change impact studies: Agriculture in the US Great Plains, 1969–1992." *Annals of the Association of American Geographers* 94(3):549-564.

Rosen, S. 1974. "Hedonic prices and implicit markets: product differentiation in pure competition." *Journal of Political Economy* 82(1): 34-55.

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

—. 2005. "Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach." *The American Economic Review* 95(1):395-406.

Schlenker, W., and M. J. Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of sciences* 106(37):15594-15598.

Shields, D. A. 2013. *Federal crop insurance: Background*. Washington DC: US Congressional Research Service Report 40532.

Smit, B., and M. W. Skinner. 2002. "Adaptation options in agriculture to climate change: a typology." *Mitigation and adaptation strategies for global change* 7(1): 85-114.

Smith, V.H. and Goodwin, B.K., 1996. "Crop insurance, moral hazard, and agricultural chemical use". *American Journal of Agricultural Economics*, 78(2), pp.428-438.

Wu, J. 1999. "Crop insurance, acreage decisions, and nonpoint-source pollution." *American Journal of Agricultural Economics* 81, no. 2: 305-320.

Zilberman, D., J. Zhao, and A. Heiman. 2012. "Adoption versus adaptation, with emphasis on climate change." *Annual Review of Resource Economics* 4(1):27-53.

Zulauf, C. 2016. "Crop Insurance Premium Subsidy Rates: A Proposed Objective Metric Based on Systemic Risk." *farmdoc daily* (6):86, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

CHAPTER 3:

THE GEOGRAPHY OF MISRATING PHENOMENON IN FEDERAL CROP INSURANCE PROGRAM

Abstract: Federal crop insurance program (FCIP) is the cornerstone of the U.S. farm safety net programs. Because of its rapid expansion, the program has been widely criticized for being a fiscal burden to the federal government. The major reason is its premium price that poorly reflects the risk of a loss. This paper offers the first attempt to quantify the scale, identify the spatial pattern and evaluate the fiscal impact of misrating the premium in the FCIP. The result reveals that at least 40% of the counties display some degree of misrating. Furthermore, the distribution of misrating displays a significant pattern of positive global spatial autocorrelation, which reflects the existence of regional clusters of FCIP ratemaking. Last but not least, we offer several suggestions to correct misrating without alleviating the fiscal burden associated to the program.

Key words: crop insurance, misrating, loss ratio, fiscal impact.

3.1 Introduction

The enactment of the *Federal Crop Insurance Reform Act* of 1994 paved the way for federal crop insurance program (FCIP) to become one of the main pillars in the current U.S. farm safety net programs. It accounts for roughly 30 to 40% of the annual total agricultural subsidies budget since 2010. Despite its growing popularity in the policy domain, its main criticism has been its high operational cost (Smith and Goodwin 2010; Zulauf 2016; GAO 2017). FCIP costs the American taxpayers on average around seven billion dollars each year, which can be seen as an unnecessary fiscal burden to the federal government. (Shields, 2015a, 2015b). Previous studies (GAO 1999, Josephson et al. 2000, GAO 2014, GAO 2015) have blamed the potentially flawed ratemaking system used by USDA, among multiple other reasons, for the unsatisfactory fiscal performance of FCIP. However, since the major reform of the crop insurance program in 1994, the current rating system can be praised for maintaining year after year the overall loss ratio at the country-level very close to one, the actuarially-fair level required by the law. Yet, significant spatial differences are present in the country.

Indeed, as can be seen from Panel A of figure 3.1 that reports the average loss ratio from 1994 to 2017, several counties display a large deviation from one. For instance, several counties in the Corn Belt, the Mississippi river delta, in West Virginia, North Carolina and the west coast display a low loss ratio. Panel B reports the number of years with positive underwriting losses over the 24-year period used in panel A. Regional differences are obvious. On the one hand, the large majority of counties have less than 2 years of losses throughout the entire period, but on the other side, some counties in North Carolina and West Virginia have received indemnity payments large than the paid premium for more than 22 years.

Even though several previous authors (Ramirez et al. 2015; Woodard and Verteramo-Chiu 2017) have speculated that the current ratemaking system is disproportionally in favor of the riskier areas, a formal study of the scale, spatial pattern and fiscal impacts of the misrating phenomenon is still missing in the literature. This paper offers to fill this gap. By analyzing over 2 million actuarial records collected by USDA's risk management agency since 1989, we discover that i) the issue of misrating prevails in the FCIP, ii) that counties with similar misrating statuses are clustered in space, and iii) that the fiscal implication of correcting misrating depends on the demand elasticity for insurance.

We organize the rest of the paper as follows. The next section offers a brief history of crop insurance as well as the structure and operation of the current program. Section 3 describes the Risk Management Agency's (RMA) ratemaking procedure, reviews the related literature, and gives an empirically testable definition of misrating. The loss ratio dataset and empirical methods adopted in this study are introduced and discussed in Section 4. Section 5 reports the results and discusses the fiscal implications of misrating. Finally, Section 6 summarizes the results and offers some concluding remarks.

3.2 Institutional Background

3.2.1 A brief history of federal crop insurance program

Initially, the crop insurance program was part of President Franklin. D. Roosevelt's "New Deal" that started in 1938 when the Federal Crop Insurance Corporation was established. Its initial aim was to help U.S. farmers recover from the double hits of the Great Depression and the Dust Bowl. It remained as an experimental program until 1980 when Congress passed the *Federal Crop Insurance Act*. The 1980 Act recognized crop insurance as one of main forms of agricultural subsidy. Even though crop insurance programs expanded quickly during the 1980s, they suffered from two important challenges: low participation rates and high loss ratios. However, the 1994 *Federal Crop Insurance Reform Act* (FIRCA) passed by Congress set the goal to extensively expand crop insurance programs and have them replace direct payment programs. The latter had been criticized for distorting the market efficiency as early as World War II. The 1994 Act increased the intensity of premium subsidy and even included a mandatory clause[13] requiring farms to purchase crop insurance in order to be eligible for other subsidy programs. This legislation paved the way for crop insurance to become the dominant component of the U.S. farm safety net programs. The year 2000 witnessed the passage of another piece of legislative milestone: the *Agricultural Risk Protection Act* (ARPA) which generously increased the premium subsidy rate for higher coverage policies. As a consequence, these higher coverage policies started to become increasingly popular among farmers.

Figure 3.2 illustrates the impacts of these legislations on both the average loss ratio (panel A) and the number of insured acreage (panel B) from 1989 to 2017. The 1994 FCIRA and 2000 ARPA divide the entire period into three stages. The first one (pre-1994) is characterized by the coexistence of a low participation rate and a high loss ratio, which reveals an adverse selection problem that triggered the major reform of 1994. Less than 100 million acres were insured and the national loss ratio was close to 1.5 for most of that period. The second stage (1995-1999) witnessed a rapid participation rate growth and the total insured acreage surged from 100 million acres in 1994 to over 220 million acres just one year later. After the 1996 setback due to the removal of the mandatory clause, the FCIP quickly regained its momentum thanks to the introduction of revenue-based policies. By the end of this stage, the insured acreage returned to a level above 200 million acres. In addition, the loss performance decreased due to multiple factors: (i) the mandatory

[13] This mandatory clause had been removed in the 1996 farm bill due to strong political resistance.

participation mitigated the impacts of adverse selection. (ii) fewer natural disasters took place in rural areas during that period (iii) most of farmers chose low coverage level policies date back to that stage. Finally, the last stage started in 2001. Thanks to increasingly generous premium subsidies from the federal government, the insured acreage kept increasing steadily to eventually exceed 300 million acres in 2017. In terms of loss performance, there is no obvious difference with the second stage besides the 2002 drought in the great plain and the east coast and the 2012 drought in the corn belt.

3.2.2 The current program in action

Figure 3.3 summarizes how the current program works. Panel A is a typical timeline in the U.S. Corn Belt. Such timeline typically varies by different crops and regions. At the beginning of each growing seasons, farmers contact a private insurance company to disclose the type of policy and the coverage level they want to buy for their crop(s)[14]. The two major types of policies available are the yield protection (YP) and the revenue protection (RP). In most cases, the choice of the coverage level ranges from 50% to 85%. In the middle of the growing season - usually June in the Corn Belt - farmers are required to report their planting acreage to their insurance company. Shortly after the harvest season, the premium is due. Following that event, farmers can claim a loss and receive indemnity payment from the insurance companies if their actual revenue is below the revenue guarantee set in their insurance policy.

Panel B describes the pivot role played by the government. Even though the government does not directly insure farmers, its actions influence profoundly the transactions between farmers

[14] They do not need to specify the exact planting acreage, therefore do not need to pay the premium at this stage.

and insurance companies from the beginning to the end of the process[15]. First, it approves new insurance products and makes the decisions on which policies can be sold in which region. Second, the government sets and dynamically updates the premium rates for all crop insurance policies. The rating procedure used by the government will be discussed in detail in the next section. Last but not least, the government provides generous subsidies to both sides. Indeed, a large proportion of the total premium is paid by the government. For example, the average subsidy rate in the Midwest is around 70%, i.e. farmers usually only pay 30% of the total premium. At the same time, the government supports substantially the private insurance companies via two channels: (i) risk sharing through standard reinsurance agreement (SRA), (ii) the reimbursement of their administrative and operating (A&O) costs.

3.3 Crop insurance ratemaking and misrating

We start this section with a summary of the ratemaking system used by USDA; then we review the literature on pricing crop insurance policies. Finally, an empirically testable definition of misrating is given and is followed by a new a statistical procedure to detect misrating based on long-run actuarial records.

3.3.1 Ratemaking system for the crop insurance program

This section presents a simplified version[16] of the actual RMA rating system. Further details are available in Woodard et al. (2011), Sherrick et al. (2014) and Ramirez et al. (2015). The current premium rating system used by USDA is established based on the loss cost rate (LCR) approach.

[15] Specifically, USDA's Risk Management Agency (RMA) is responsible for managing and operating while the Federal Crop Insurance Corporation (FCIC) is involved in the business relationship with private insurance companies and individual farmers.

[16] Coble et al. (2010) is, by far, the most comprehensive document in the public domain to discuss the premium rating procedure.

In essence, LCR determines the premium rate based on historical loss performance. The worse loss performance in the past leads to higher premium rate in the future and vice versa.

In order to determine the premium for an individual farmer given a specific crop, the RMA takes a two steps approach. First, it determines the county base rate by averaging the previous multiple years' loss cost rates at county level. And the county LCR is defined as the ratio of indemnity to liability for a given year. Eq. (3.1) formally describes the ratemaking process ρ_T^c for a county c and a period T as follows:

$$\rho_T^c = \frac{1}{T}\sum_{t=0}^{T-1}\underbrace{\left(\frac{\text{Indemnity}_{ct}}{\text{Liability}_{ct}}\right)}_{\equiv \text{LCR}_{ct}} = \frac{1}{T}\sum_{t=0}^{T-1}\left(\frac{\sum_i \max(0, \text{cov}_i \cdot \text{APH}_{it} - Y_{it})}{\sum_i \text{cov}_i \cdot \text{APH}_{it}}\right) \tag{3.1}$$

where t is an index for time and i is each individual farmer whose land is in the county c. Indemnity is defined as the total indemnity payment to all farmers across the county. The indemnity is positive when the actual yield (Y) is below the guaranteed yield. More precisely, it is equal to the farmer-chosen coverage rate (cov) multiplied by his/her approved actual production history (APH) yield defined as the average of the last 4-10 years (Plastina and Edwards, 2017). Similarly, the liability is calculated by summing up all the farmers' yield guarantee over the entire county. Note that we normalize the crop price to one for simplicity purposes.

The second step consists in adjusting the individual farmer's premium rate ρ_T^i based on the farmer's approved APH yield using a "shrinkage" factor, that is:

$$\rho_T^i = \rho_T^c \cdot \left(\frac{\text{APH}_{iT}}{Y_T^c}\right)^{\gamma} \tag{3.2}$$

where Y_T^c is the county average yield and γ is a policy coefficient set by RMA. It usually ranges from -2 to -4, which allows farmers to get a lower premium rate if his/her approved APH yield is higher than the county average yield and vice versa.

3.3.2 Related literature on ratemaking for crop insurance

"Correctly" setting the crop insurance premium rate has been one of the central questions of the agricultural economics literature since the inception of the system. The earliest attempt is Botts and Boles (1958) who advocated for calculating the crop failure probability based on the left-tail behavior of normal distribution. A few years later, Yeh and Wu (1966) criticized the normal distribution assumption and suggested to incorporate the impact of technological and weather factors on crop yield.

The period from mid-1980s to early 1990s witnessed an increasing number of contributions on ratemaking as the program expanded rapidly and the loss performance was high (see Fig. 1). The two most cited contributions are Skees and Reed (1986) and Goodwin (1994). The first one introduced the concept of adverse selection into the debate of optimal ratemaking for crop insurance while the second one constitutes the first effort to capture the role of production heterogeneity among farmers in the calculation of the premium rate.

The academic interest in understanding the FCIP ratemaking grew even more after the massive expansions of the program due to the passage of the 1994 (i.e. FCIRA) and 2000 (i.e. ARPA) Acts. Two schools of thoughts try to address the definition of the appropriate rate premium. The first one aims at finding the more realistic distribution for yield modeling. Classic contributions in this area include but are not limited to Ramirez (1997) on flexible parametric distribution, Goodwin and Ker (1999) on nonparametric estimates and Sherrick et al. (2004) on comparison among different yield distributions. More recently, researchers started to incorporate both spatial correlation (Annan et al., 2013; Goodwin and Hungerford, 2014) and technological changes (Zhu et al., 2011; Tolhurst and Ker, 2014) into the modelling of the yield distribution.

The other approach consists in detecting the flaws present in the current rate system. For example, Babcock et al. (2004) blame the constant rate relativities[17] between high- and low-coverage policies for overpricing the high coverage policies. Woodard (2011) casts doubt on the dynamic updating of loss cost rates. Ramirez et al. (2015) focus on the "shrinkage" factor approach used by RMA to adjust individual farmers' rate based on their APH. More recently, Woodard started to advocate for the utilization of fine-resolution soil data to improve the pricing of FCIP by taking into account the intra-county productivity difference among farmers (Woodard, 2016; Woodard and Verteramo-Chiu, 2017). The spatial characteristics of the data, spatial heterogeneity and spatial autocorrelation, have caught the attention of scholars in this area as early as Glauber (2004). These phenomena, based on the spatial association in the distribution of the weather and soil characteristics (Ezcuerra et al., 2008; Dall'erba and Dominguez, 2016), can lead to biased and inconsistent estimates if not controlled for appropriately (LeSage and Pace, 2009). Since Glauber (2004), only Woodard et al. (2012) and Sherrick et al. (2014) have explored this research direction further. The former contribution uses spatial econometric techniques to study if the regional difference of loss experience in the U.S. Midwest can be explained by several flaws in the ratemaking system. The second one, on the other hand, offers a detailed exploratory data analysis of the historical loss experience, rating and risk sharing structure among the major U.S. crop insurance programs.

3.3.3 Misrating definition and detecting strategy

RMA is required by the *Federal Crop Insurance Act* (7 U.S.C 1508(d)(1) and related) to set county-specific actuarially-fair premium rate for each individual crop. Therefore, in the case of

[17] Constant rate relativities are the set of ratios used by USDA RMA to pricing the non-65% coverage policy based on the premium of 65% coverage policy which serves as the kernel of the ratemaking system.

crop insurance, misrating should be defined as any systemic difference between the existing premium rate and its actuarially-fair target. The latter is usually defined as the premium rate offering the full insurance to the insured. Formally, it is equal to the expectation of the loss cost ratio.

For the purpose of formally testing the existence of misrating, it is useful to rewrite the definition of actuarially-fair policies in terms of loss ratio (i.e. the ratio of indemnity to pre-subsided premium) as in Eq. (3.3) below and to notice that an insurance policy is priced at its actuarially-fair rate (ρ_{af}) if and only if the expectation of the loss ratio is equal to one.

$$\rho_{\mathrm{af}} \equiv \mathbb{E}\left(\frac{\text{Indemnity}}{\text{Liability}}\right) \Leftrightarrow \mathbb{E}\underbrace{\left(\frac{\text{Indemnity}}{\rho_{\mathrm{af}} \cdot \text{Liability}}\right)}_{\text{loss ratio}} = 1 \tag{3.3}$$

According to the law of large numbers, the sample mean of the loss ratio approaches its expectations as the sample size increases, which suggests that the presence of misrating would be confirmed if the long-run average loss ratio for a given policy is systemically and significantly different from one. However, in order to confirm the above hypothesis, one hidden assumption has to be valid: the distribution of the loss ratio should be constant over time, which unfortunately cannot be tested using the existing data. However, LCR rating approach adopted by RMA, to some extent, is trying to avoid the loss ratio distribution evolving by allowing premium rate catching up with the temporal variation of the indemnity.

3.4 Data and empirical models

This section starts with a description of the loss ratio data source and its summary statistics. It continues with three statistical tests of the presence of misrating as discussed in section 3.3 and ends with several tests assessing if misrating is a spatially autocorrelated variable.

3.4.1 Summary of Business from USDA RMA

The main data source available in the public domain for crop insurance information is USDA's RMA Summary of Business (SOB). It contains detailed actuarial information of crop insurance policies at the county level dated back to early 1980s. For the current study, we collect the insured acreage, liability, premium, government subsidy, indemnity and loss ratio by different crops, the insurance plans and coverage categories for each county in the continental U.S. from 1989 to 2017. We choose 1989 as the starting year as the record layouts[18] are the same for all the years post-1989.

Based on the raw records, we generate the time series of loss ratios from 1989 to 2017 for each segment of crop insurance policies. A segment is defined as a group of policies sold in one county for the same specific crop, insurance plan and coverage level. The final dataset contains over 2 million data points which are grouped into 212,373 segments. On average, there are roughly 10 records per segment and 72 segments per county. We calculate the overall loss ratio for each county for each year by averaging loss ratio records for all crops, insurance plan, coverage levels sold in that county. The liability of each type of policies is used as the weighting scheme. Almost 90% (2,605 out of 2,960)[19] of the counties have more than 20 years of observations. On the other hand, only 6% (189 out of 2,960) of the counties possess less than 10 years of record.

Figure 3.4 displays some summary statistics. Panel A reports the histogram and empirical density estimates of counties' average overall loss ratio from 1994 to 2017. The blue dashed line indicates the actuarially-fair loss ratio (i.e. 100%). Even though a large proportion of counties do not display a loss ratio close to one, several counties are located in the left and right tails of the

[18] The current record layout can be retrieved from RMA's website: https://www.rma.usda.gov/-/media/RMAweb/SCC-SOB/State-County-Crop-Coverage/sobsccc_1989forward-pdf.ashx?la=en

[19] The number of counties where crop insurance data (2,960) is available is less than the total number of counties in the lower 48 states (3,107).

distribution. Since the left tail of the distribution is bounded at zero, the more extreme values appear in the right tail. The boxplots of the average loss ratios for four main insured crops (corn, cotton, soybeans and wheat) are listed in panel B. For any crop, the number of counties with less-than-one loss ratios (horizontal blue dotted line) is greater than those with larger-than-one loss ratios. In the case of corn and soybean, almost 75% of the counties have loss ratios below the actuarially-fair level. For cotton and wheat, that percentage is slightly above 50%. Last but not least, panel C lists the boxplots for four main coverage levels: 55%, 65%, 75% and 85%. Two points are worth noting. First, the median of the loss distribution increases with the coverage level. In particular, it increases from 63% for the 55% coverage level to 97% for the 85% coverage level. Second, the variances of 0.65 and 0.75 coverage policies are less than the variances of the 55% and 85% coverage policies.

3.4.2 Three statistical tests for detecting misrating counties

Three statistical tests can be used to examine whether the long-run average loss ratio is significantly different from 1. These are the one-sample Student's t-test, the Wilcoxon's signed-rank test and the bootstrap method. The Student's t-test is the standard parametric routine to test the significance of the sample mean differ from its theoretical prediction. Its validity relies on whether the sample was drawn from a Gaussian distribution or whether the sample size is large enough. The rule of thumb here is usually that the sample size should be above 30 observations.

When the t-test conditions cannot be satisfied, two non-parametric methods can be used (Dalgaard, 2002; Crawley, 2005) The first method is the Wilcoxon's signed-rank test (Noether, 1991) which can be formulated as follows:

$$T = \sum_{i:x_i > m} \mathrm{rank}(|x_i - m|) \tag{3.4}$$

The Wilcoxon procedure first ranks all the observations based on their distance to the hypothetical mean (m) and then sums up all the ranks associated with the observations which are larger than m. Large values of T reject the null hypothesis of absence of misrating (long-run average loss ratio equal to 1). The Wilcoxon test requires the sample to draw from a symmetric distribution. In practice, this requirement can be easily fulfilled by a logarithm transformation of the original dataset.

The third option is bootstrapping. This method generates a large number of random samples by bootstrapping the original data set with replacement and then calculating the mean for each new sample. The calculated mean can be compared with the hypothetical mean (1 in our case) within a pre-determined (e.g. 95%) confidence interval.

While the presence of misrating is our null hypothesis in the tests above, it is important to distinguish the singular effect of overrated vs. underrated counties because of the opposite fiscal implications they have on the CFIP program. Indeed, on average, overrated counties contribute to underwriting gains while underwriting losses most likely occur in the underrated counties. In order to distinguish these two types of misrating, we will conduct a one-sided t-test and Wilcoxon procedure where the alternative hypothesis is "strictly lesser (or larger) than one". For the case of bootstrap, the underrated sample mean will be compared with the 5% quantile value of the 10,000 bootstrapped mean values while the above-one sample mean will be compared with the 95% quantile value.

3.4.3 Spatial statistics for diagnosing spatial autocorrelation

Last but not least, the possible presence of spatial association in the distribution of misrating across counties needs to be assessed in order to discover whether misrating in one county significantly influences misrating in nearby counties (Getis and Ord, 1992; Bivand et al., 2008). If it were to be the case, then the political boundaries currently used to calculate the premium rate may be misleading and a multi-county definition criterion may be more relevant.

The variable of interest is a categorical variable with three values: “fairly rated”, “overrating”, and “underrating”. Join-counts statistics, particularly the join-counts statistics for k-colored map (k = 3) is a measurement of spatial association based on counting the number of joins, i.e. the number of cases where two polygons with a similar color pattern are nearby (O'sullivan, and Unwin 2014; Dale and Fortin 2014; and Plant 2018). Cliff and Ord (1981) have defined the following statistics for a two-category case (black B and white W):

$$\text{(3.5)} \qquad \mathrm{BB} = \frac{1}{2}\sum \mathrm{w}_{\mathrm{ij}}\mathrm{x}_{\mathrm{i}}\mathrm{x}_{\mathrm{j}} \quad \text{and} \quad \mathrm{BW} = \frac{1}{2}\sum \mathrm{w}_{\mathrm{ij}}\left(\mathrm{x}_{\mathrm{i}} - \mathrm{x}_{\mathrm{j}}\right)^2$$

where BB stands for the join between counties with the same color and BW stands for the join between counties of two different colors. An extension to the k>2 case is straightforward by identifying B to one category and W to the other categories. w_{ij} is the (i,j) element in the spatial weight matrix of which value is 1 when county i and j are neighbors and 0 otherwise. As a result, the BB statistics increases when two neighboring counties share the same color. Similarly, the BW statistics increases when neighboring counties belong to a different category. The calculated values of BB or BW can be compared to their expected values and associated standard errors (under the null hypothesis of random distribution) in order to draw statistical inference[20].

Besides join-counts test, Moran’s I is arguably the most commonly used statistics for detecting spatial autocorrelation for lattice/polygon data. However, the standard version of Moran’s I is not suitable for the current analysis for the following two reasons: first, the standard Moran’s I is designed for continuous variables. While this technical difficulty can be bypassed by

[20] Zhang and Zhang (2008) derive the first and second moment of joint count statistics for the 3-color map (i.e. black, white and grey). Readers who are interested in the exact formula for these moments can directly refer to their paper.

assigning a numerical value to each category, such transformation could be problematic since it imposes unnecessary ranking on the categories. For instance, if we were to assign 3 to “underrated”, 2 to “overrated” and 1 to “fairly rated”, we would assume that the first category is literally three times the value of the last one, which does not make sense. The second reason is related to the assumption of linear spatial correlation embedded in Moran’s I (Farber et al. 2015). Indeed, Moran’s I can be interpreted as the Pearson coefficient between a (standardized) random variable and its spatial lag.

Join-count statistics, on the other hand, do not impose this restriction as they are a nonparametric method. However, they must be conducted for each pair of the categorical level. In our case, the misrating status has 3 levels so one must construct and run 6 separate test statistics. When the total number of categorical level increases, the join-counts analysis can quickly become cumbersome. Furthermore, there is no clear way to correct the multiple testing issue as the test statistics calculated for different pairs of categorical levels are usually non-independent (Epperson 2003). In order to overcome this shortcoming, Lee and Ogburn (2018) propose the following statistic to measure global spatial dependence across categorical variables:

$$\Phi = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \{2\mathbb{I}(y_i = y_j) - 1\} / p_{y_i} p_{y_j}}{S_0} \tag{3.6}$$

where i and j are indices for spatial units in the sample of size N; y_i and y_j are two realizations of a K-level categorical random variable Y for two individuals; $\mathbb{I}(y_i = y_j)$ is an identity function of which value is one when the realizations are concordant for two regions and zero otherwise. p_{y_i} and p_{y_j} are the probability that this random variable takes these respective two levels. Finally, S_0 is a normalization constant equal to $\sum_{i=1}^{N}(w_{ij} + w_{ji})/2$. It measures the total number of links defined in a given weight matrix. The term $\{2\mathbb{I}(y_i = y_j) - 1\}$ in the numerator generates a score (or signal) measuring the level of spatial association. More precisely, when $y_i = y_j$ (i.e. when two neighboring regions are in the same category), then the score is equal to 1, hence providing evidence of positive spatial autocorrelation. The score is -1 when two regions are in different categories, which reflects negative spatial autocorrelation. The product of the two probabilities p_{y_i} and p_{y_j} in the denominator give the less probable pairs a larger weight in the calculation of the statistics. In our case, the "underrated-underrated" pair will be given a larger weight compared to the "overrated-overrated" pair as the former appears more rarely in the sample. The Φ statistics is thus a measurement of the average of the spatial association scores generated by each data point that is weighted inversely by its probability of occurrence.

Lee and Ogburn (2018) claim that Φ is based on the logic of the traditional Moran's I defined as follows:

$$T = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} F(y_i, y_j)}{S_0}$$

where $F(y_i, y_j)$ is a function of the values associated with two spatial units. The difference between the above two measures is the choice of the $F(\cdot)$ function. Compared to the statistics in Eq. (3.6), Moran's I sets $F(y_i, y_j) = \frac{(y_i - \bar{y})(y_j - \bar{y})}{\sum_i^N (y_i - \bar{y})^2}$. Furthermore, Lee and Ogburn (2018) prove that when y follows a Bernoulli distribution then the standardized version of the two measures are equivalent. In addition and similarly as Moran's I, the sign of Φ indicates either positive or negative spatial autocorrelation while the absolute value of Φ indicates the magnitude of the spatial association. When it comes to statistical inference, Lee and Ogburn (2018) suggest a premutation approach which is also the most frequently used approach for Moran's I.

3.5 Results and fiscal implications

3.5.1 Testing the misrating status based on the overall loss ratio

Figure 3.5 reports the number of counties by their tested misrating status based on their overall loss ratio. Counties with a loss ratio that is statistically less than (more than and equal to) 1 are labeled as "overrated" ("underrated" and "fairly rated" respectively). The results, based on all three methods, confirm that misrating concerns around half of the FCIP counties (60% when based on Wilcoxon test).

We also note that the large majority of the misrated counties are "overrated". In order to fully appreciate the fiscal implications of this phenomenon, we must combine this result with the fact that the nation-wide long-run loss ratio for the entire FCIP is close to one. It means that, on average, the underwriting gains collected from the substantially large group of "overrated" counties are offset by the underwriting loss that occurs in the much smaller group of the "underrated" counties.

Figure 3.6 reports the maps of the misrating status associated with the three methods described earlier. The color scheme is the same as in figure 3.5, except that some counties are colored in grey to represent their misrating status are unavailable. These NA counties have a record of loss ratio that is below 10 years, the minimal data requirements for conducting reliable testing procedures.[21] These maps reveal several regional patterns. First, the overrated counties are mostly located in the Midwest, the Mississippi River Delta and the Western coast. Second, the counties in the Great Plain are more likely to have actuarially-fair ratings. Third, Texas and more especially the Appalachian states of West Virginia and North Carolina have the highest density of underrated counties in the nation.

[21] Our result is robust if the minimal data requirement raises up to 20 as over 90% of the counties have more than 20-year loss ratio record.

3.5.2 Testing the misrating status based on the segmented loss ratio

Figure 3.7 displays the count of misrating counties based on the loss ratios segmented by the four major crops (corn, cotton, soybeans and wheat) and by the four most commonly selected coverage levels. The results reveal substantial heterogeneity among the different segments. First, soybean and corn seem to suffer from overrated crop insurance policies more frequently than the other two crops no matter the coverage level. For soybean, the number of overrated counties outnumbers by 2 to 1 the number of fairly rated counties. In addition, the proportion of underrated counties is lesser in the soybean and corn categories. For cotton and wheat, fairly rated counties outnumber the other two types. Yet, we note an extreme case whereby the number of overrated counties is less than that of underrated counties for cotton policy and an 85% coverage level.

Comparing various coverage levels across different crops generates additional and useful insights. First, the 65% coverage policies which are used by RMA as the benchmark for pricing other coverages do not seem to outperform other policies in terms of misrating rate. Babcock et al. (2004) assume that the 65% coverage policies should be actuarially-fair. However, their hypothesis cannot be confirmed by the long-run actuarial data. Second, the probability of being overrated decreases as the coverage level increases. If one takes corn as an example, the ratio of overrated counties drops from 64% for the 55% coverage to 47% for the 85% coverage. A similar pattern is found for the other three crops. Third, the higher coverage policies are more likely to be underrated. For instance, the ratio of underrated counties for the wheat policies increases from 1% for the 55% coverage to 11% for the 85% coverage. This pattern holds true for almost all the cases. The only exception is that the 65% coverage has the highest underrated ratio among all the soybean policies.

3.5.3 The geographic characteristics of the misrating status

Figure 3.8 summarizes the spatial distribution of misrating counties over the ten farm production regions. These regions can be segmented into three groups. The first one contains four regions, namely the Corn Belt, the Lake states, the Delta states and the Pacific region. The similarity they share is in the number of overrated counties that is considerably larger than the number of fairly rated counties. Underrated counties are almost inexistent in that group. The regions Mountain, Northeast and the Northern Plains constitute the second group. What characterizes this group is the adequately balanced numbers of overrated and fairly rate counties. Very few underrated counties are present in the second group too. The third group, on the other hand, is home of over 90% of the nation's underrated counties. Three southern regions are in this group, namely the Appalachia, the Southeast and the Southern Plains. Another important feature of this group is the large number of fairly rated counties compared to the overrated counties. Overall, the presence of these clustering patterns indicates the existence of positive spatial association which we propose to formally test below using the Join-count statistics.

Table 3.1 presents the results of the Join-count test for spatial autocorrelation. Recall that there are three different misrating statuses, which implies six different possible pairing options. Row (1) to (6) in the table show the Join-count statistics associated with each of them. Row (7), termed "Jtot", is the Join-count statistics for the total number of joins between counties of different colors regardless of how dif. The first column reports the Join-count statistics calculated from the data. The expected value and the variance under complete spatial randomness are displayed in the second and third columns. The final column reports the z-value, i.e. the difference between the sample Join-count and its theoretical expectation divided by the squared-root of its variance. The rule of thumb for rejecting the null hypothesis at the 95% confidence threshold is that the numerical value of z is greater than 2.

The z-value for all three BB statistics (listed in the first three rows in the table) is close to or greater than 30, which indicates significant positive spatial autocorrelation. The results for the BW statistics are less consistent. Two out of the three statistics, namely overrated-fairly_rated and underrated-overrated and Jtot, have negative and significant z-values, which again reveals the presence of positive spatial autocorrelation. On the other hand, the underrated-fairly_rated joins, most likely to be seen in the Appalachia area (figure 3.6), suggests the existence of negative autocorrelation, as this type of discordant joint (426 cases) appear more frequently than it should be under spatial independent assumption. Therefore, we apply Lee and Ogburn's Φ to provide an omnibus test on the sample. A significant positive Φ (= 38.76) with p-value (premutation) = 0.001 finally confirms the strong positive spatial association among misrating status.

3.5.4 Fiscal implication of crop insurance misrating

Now that we have highlighted the presence, size, geographical distribution and spatial association of misrating in FCIP, one natural follow-up question is whether the government can save taxpayers' money by correcting the misrating in FCIP. In that purpose, we develop a simple two-county model to cast some light on this issue.

Assume a two-county economy, A and B, where $\tilde{p}^A$ and $\tilde{p}^B$ are their respective actuarially-fair rates. Further assume the current premium rate in county A is larger than its actuarially-fair rate ($p^A > \tilde{p}^A$, so county A is overrated) while the current premium in county B is less than its actuarially-fair rate ($p^B < \tilde{p}^B$ so county B is underrated). The objective equation of the government is to minimize the following total outlay (TO) paid for the program:

$$\mathrm{TO} = \underbrace{\delta(p^A L^A + p^B L^B)}_{\text{premium subsidy}} + \underbrace{\mu(\mathbb{E}(I^A + I^B) - p^A L^A - p^B L^B)}_{\text{underwriting gain/loss share}} + \underbrace{\gamma(p^A L^A + p^B L^B)}_{\text{A\&O reimbursement}} \tag{3.7}$$

The total outlay is composed of three elements. The first element is the premium subsidy where δ is the subsidy rate and L is the liability. The second element is the government underwriting gain/loss under standard reinsurance agreement with μ as the loss sharing ratio, and I is the indemnity. The third term is the A&O reimbursement to private crop insurance companies which is usually a percentage (γ) of the total premium. In addition, we assume that the loss ratio for the entire program must be equal to one, which is both required by law and reflects reality. To sum up, the government's problem is to minimize Eq. (3.7) subject to the following constraint:

$$\frac{\mathbb{E}(\mathrm{I}^{\mathrm{A}} + \mathrm{I}^{\mathrm{B}})}{\mathrm{p}^{\mathrm{A}}\mathrm{L}^{\mathrm{A}} + \mathrm{p}^{\mathrm{B}}\mathrm{L}^{\mathrm{B}}} = 1 \tag{3.8}$$

Substituting Eq. (3.8) into Eq. (3.7), we can simplify the objective function to:

$$\mathrm{TO} = (\delta + \gamma) \cdot \left(\sum_{\mathrm{i} \in \{\mathrm{A},\mathrm{B}\}} \mathrm{p}^{\mathrm{i}}\mathrm{L}^{\mathrm{i}} \right) \tag{3.9}$$

Eq. (3.9) implies that reducing the total outlay requires the total premium to be reduced. Recall that the relationship between liability and the premium rate is defined by a demand function of insurance $\mathrm{L}^{\mathrm{i}} = \mathrm{D}^{\mathrm{i}}(\mathrm{p}^{\mathrm{i}})$.[22] Hence, the total premium of county i, $\mathrm{p}^{\mathrm{i}}\mathrm{D}^{\mathrm{i}}(\mathrm{p}^{\mathrm{i}})$, is the total insurance revenue in this case.

The original question of whether correcting misrating reduces the operational cost of FCIP can be answered by taking the total derivative of Eq. (3.8) with respect to the premium rates p^{i}.

$$d\mathrm{TO} = \underbrace{(\delta + \gamma)}_{+} \cdot \left[\left(\frac{\partial \mathrm{p}^{\mathrm{A}}\mathrm{D}^{\mathrm{A}}(\mathrm{p}^{\mathrm{A}})}{\partial \mathrm{p}^{\mathrm{A}}} \right) \underbrace{d\mathrm{p}^{\mathrm{A}}}_{-} + \left(\frac{\partial \mathrm{p}^{\mathrm{B}}\mathrm{D}^{\mathrm{B}}(\mathrm{p}^{\mathrm{B}})}{\partial \mathrm{p}^{\mathrm{B}}} \right) \underbrace{d\mathrm{p}^{\mathrm{B}}}_{+} \right] \tag{3.10}$$

---

[22] We add the superscript i to the demand function as well to indicate that overrated and underrated counties i may have different demand functions.

First, δ and γ are two positive policy parameters, so their sum must be positive too. Second, since county A is overrated by assumption, correcting its misrating requires to reduce its premium rate, i.e. $d\mathrm{p}^{\mathrm{A}} < 0$, and inversely for county B ($d\mathrm{p}^{\mathrm{B}} > 0$). The only two terms in Eq. (3.9) whose signs are undetermined are the two partial derivatives. Their sign is determined by the demand elasticity of the two counties. If the demand is elastic, then the partial derivative is negative and vice versa[23].

The demand elasticity of crop insurance has been studied for decades (Goodwin, 1993; Goodwin and Simth, 1995; Coble and Knight, 2002) and some estimates suggest that the demand for crop insurance in riskier areas is more elastic than in safer areas. One possible explanation is that demand for crop insurance is highly price elastic. Since the premium rates in the riskier areas are usually higher than those in safer areas, the price elasticity of demand should also be greater in riskier areas. Furthermore, since the overrated counties are usually located in safer areas such as the Corn Belt while the underrated counties are more likely in riskier areas such as the Appalachia (see figure 3.6), it is reasonable to assume that the demand in overrated counties is inelastic while the demand in underrated counties is elastic. As a consequence, the term into brackets is negative. It means that correcting the misrating by increasing the premium price in riskier areas should lead to a reduction in the total operational cost of the program.

3.6 Conclusions and Future Research

This paper documents the scale, pattern and fiscal implications of misrating the premium in the federal crop insurance program. By collecting over 2 million actuarial records from USDA's Risk Management Agency and applying a formal statistical approach, our results confirm the significant prevalence of misrating in the distribution of insurance programs across all crops as well as for the

[23] This claim and its intuitive explanation can be easily found in any introductory textbooks such as Mankiw (2016). Furthermore, the formal proof of the statement is often offered by calculus-based microeconomics textbooks, to name one, Varian (2014).

four major crops (corn, soybean, wheat, cotton). Furthermore, we detect the significant presence of positive spatial autocorrelation in the counties' misrating status ("overrated" and "underrated") which indicates regional clusters of loss experience and that the boundaries of a group of counties, rather than of each specific county, may be more appropriate to define a premium. Last but not least, the paper offers a model suggesting that reducing the total outlay of the crop insurance is feasible only under certain elasticity conditions.

Our results highlight the need to explore further the factors at the origin of misrating. Even though the existence, spatial distribution and spatial autocorrelation of misrating has been confirmed in the current study, the underlying mechanisms that lead to this phenomenon remain unknown. When it comes to crop insurance, one promising endeavor is to investigate the role of the cause of a loss as reported in the RMA dataset. Recent contributions such as Annan and Schlenker (2015) and Chen and Dall'erba (2019) indicate that farmers are much less likely to adapt to changing climate conditions and unexpected extreme weather events when their crop is insured, hence the geographical distribution of such events may be reflected in the spatial patterns of insurance claims and of the observed misrating across counties.

Figures and Tables:

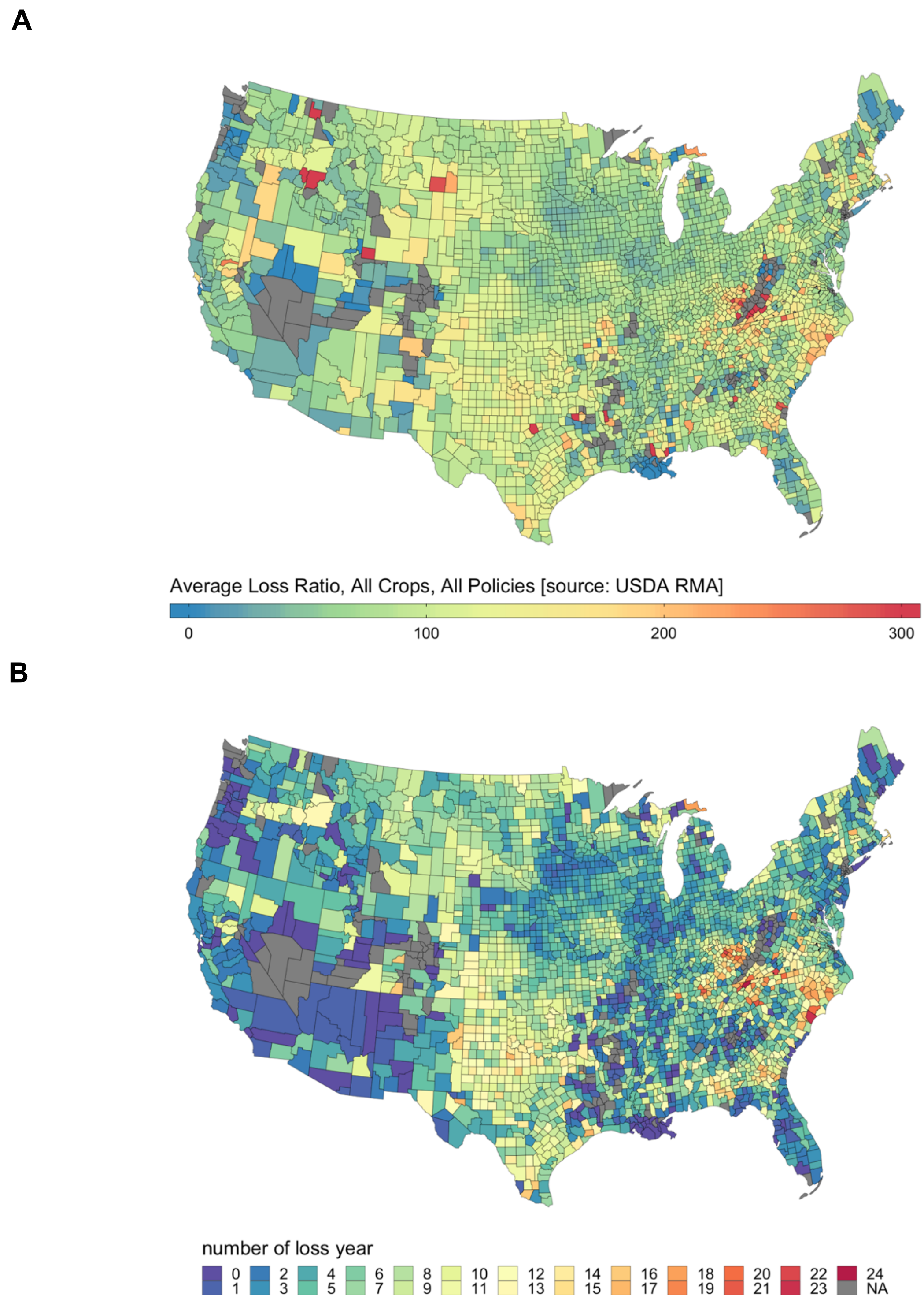


FIGURE 3.1 LONG TERM LOSS RATIO AND LOSS HISTORY MAP

FIGURE 3.2 TIME SERIES OF INSURED ACREAGE AND AVERAGE LOSS RATIO SINCE 1989

Note: The loss ratio in Panel A is presented in %.

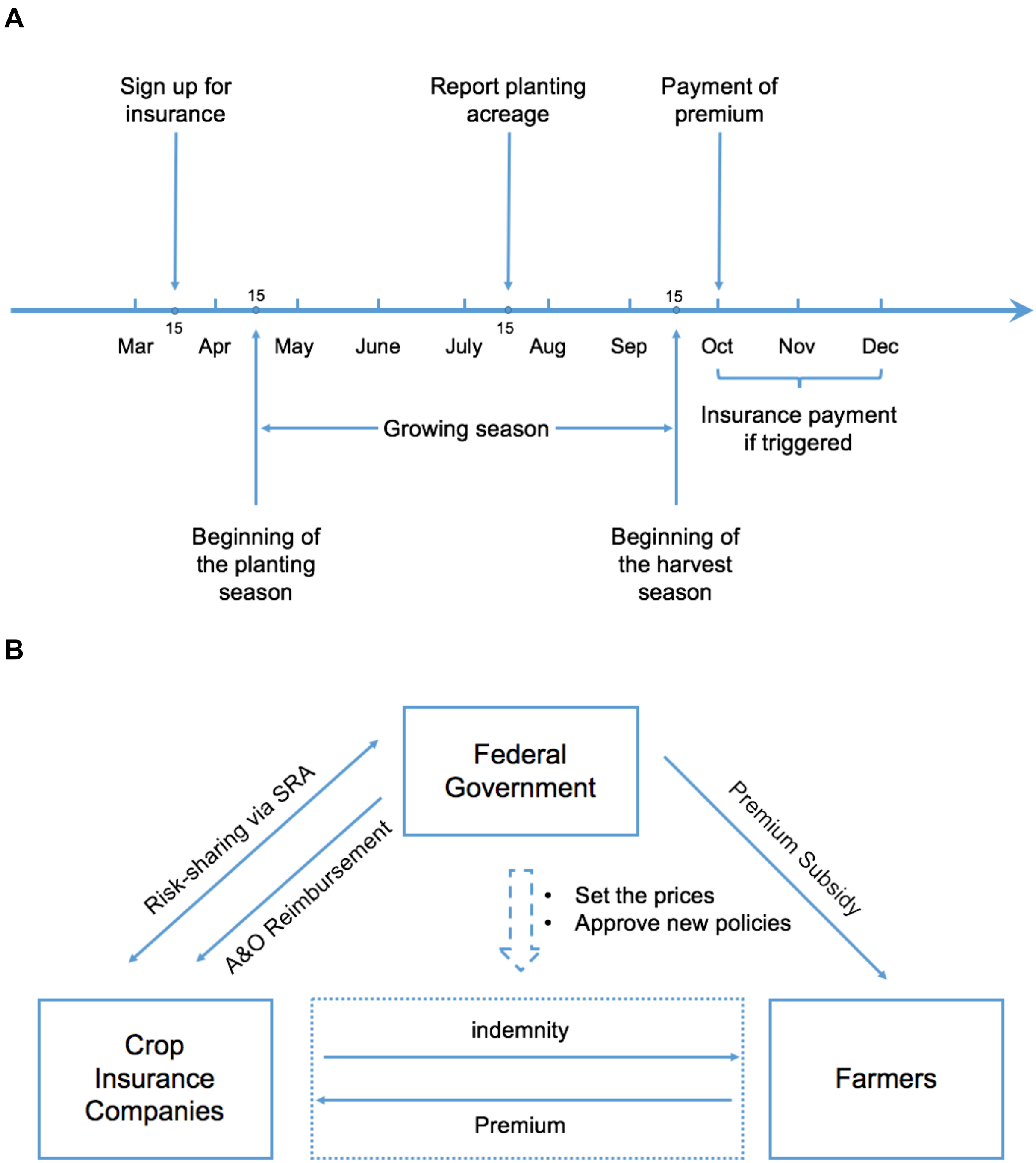
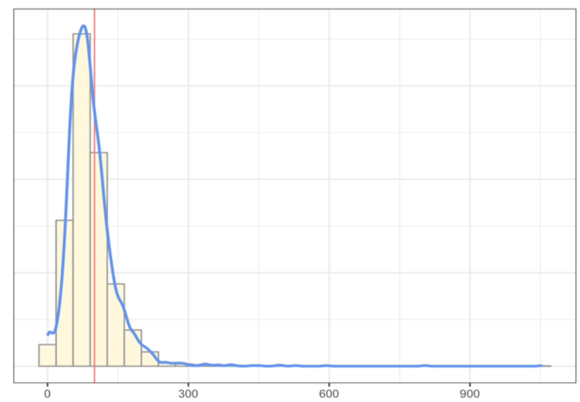
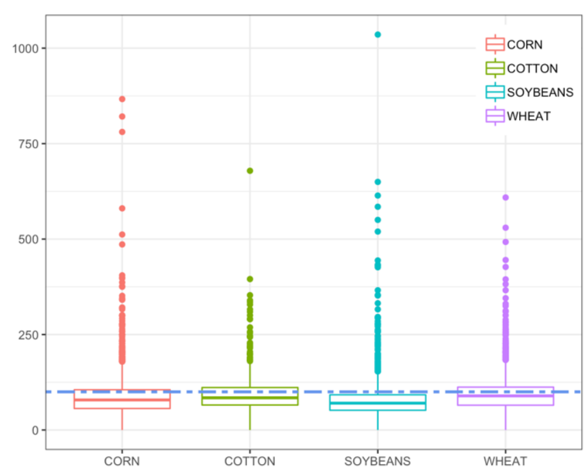


FIGURE 3.3 A SUMMARY OF CURRENT CROP INSURANCE PROGRAM

A



B



C

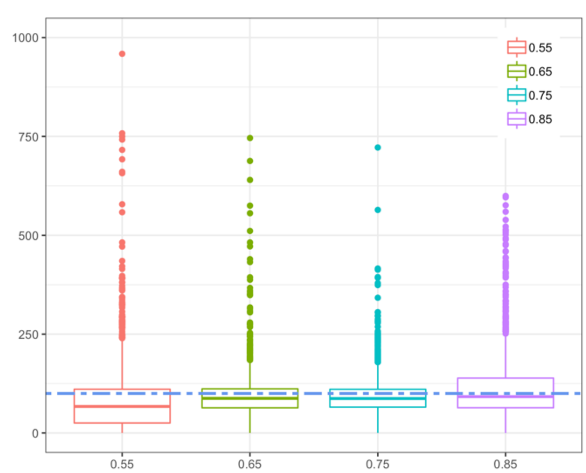


FIGURE 3.4 BOXPLOTS OF THE LOSS RATIO OF FOUR MAJOR CROPS AND DIFFERENT COVERAGE LEVELS

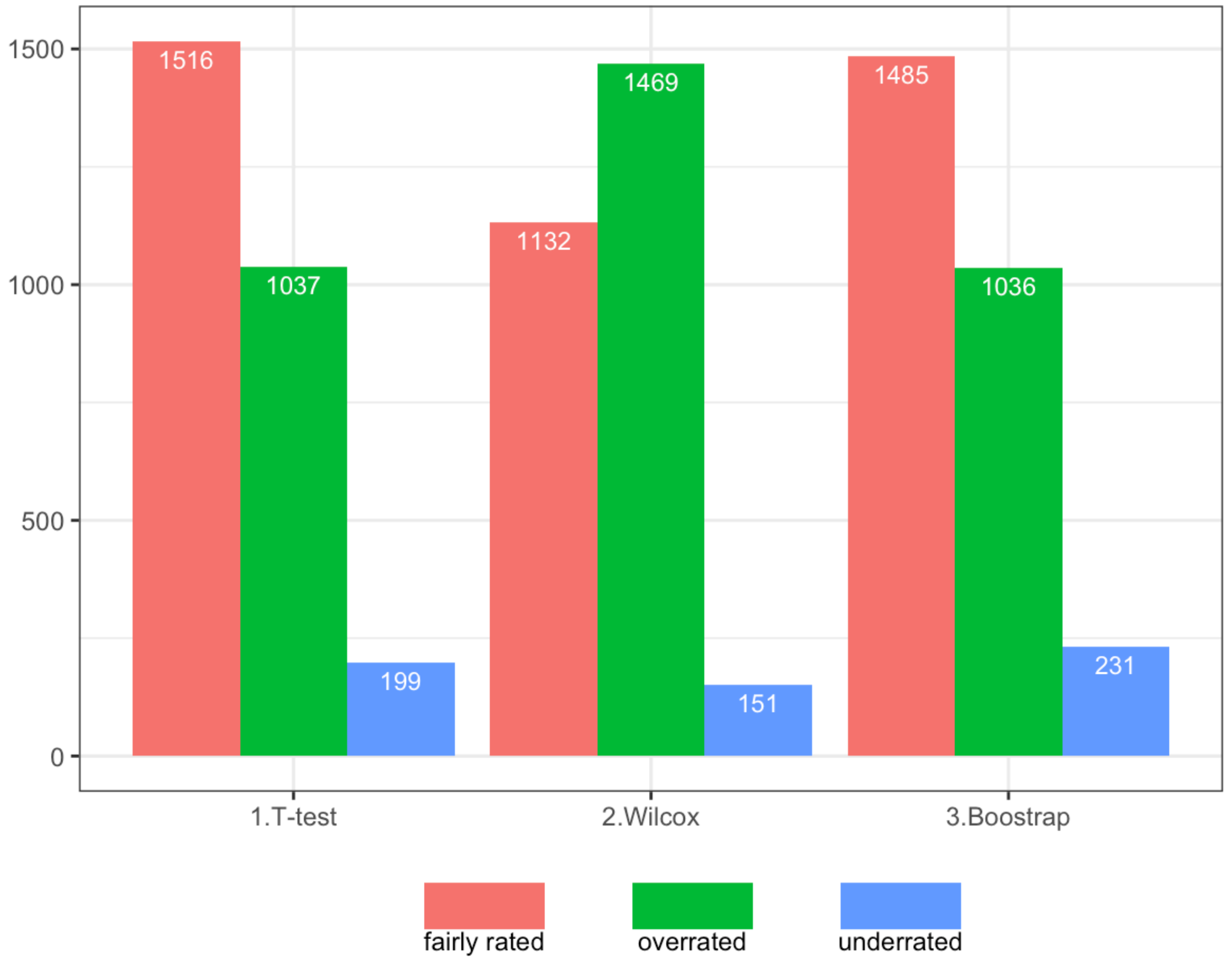


FIGURE 3.5 COUNTS OF MISRATING COUNTIES BASED ON THREE DIFFERENT METHODS

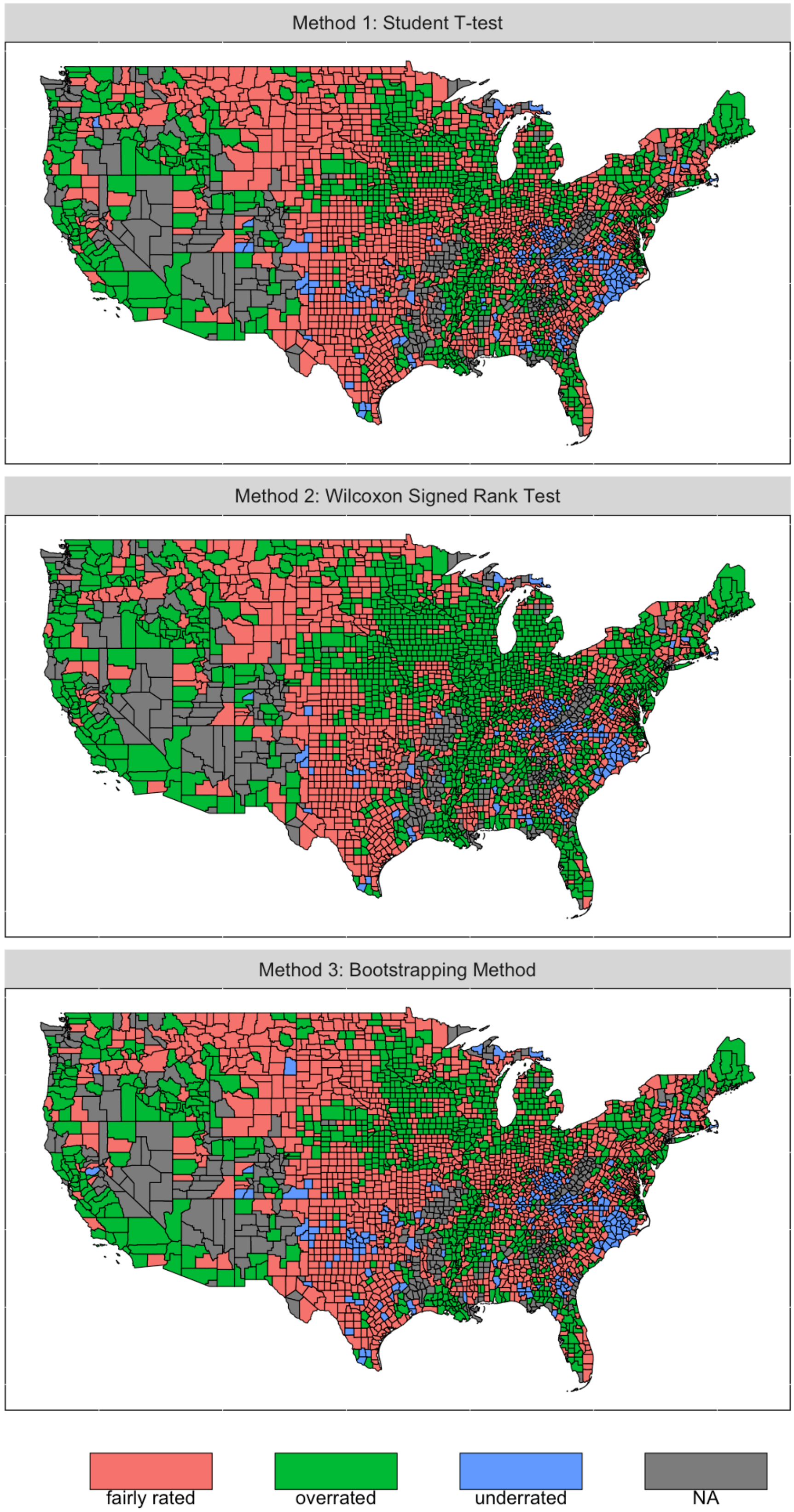


FIGURE 3.6 MAPS OF THE SPATIAL DISTRIBUTION OF MISRATING COUNTIES

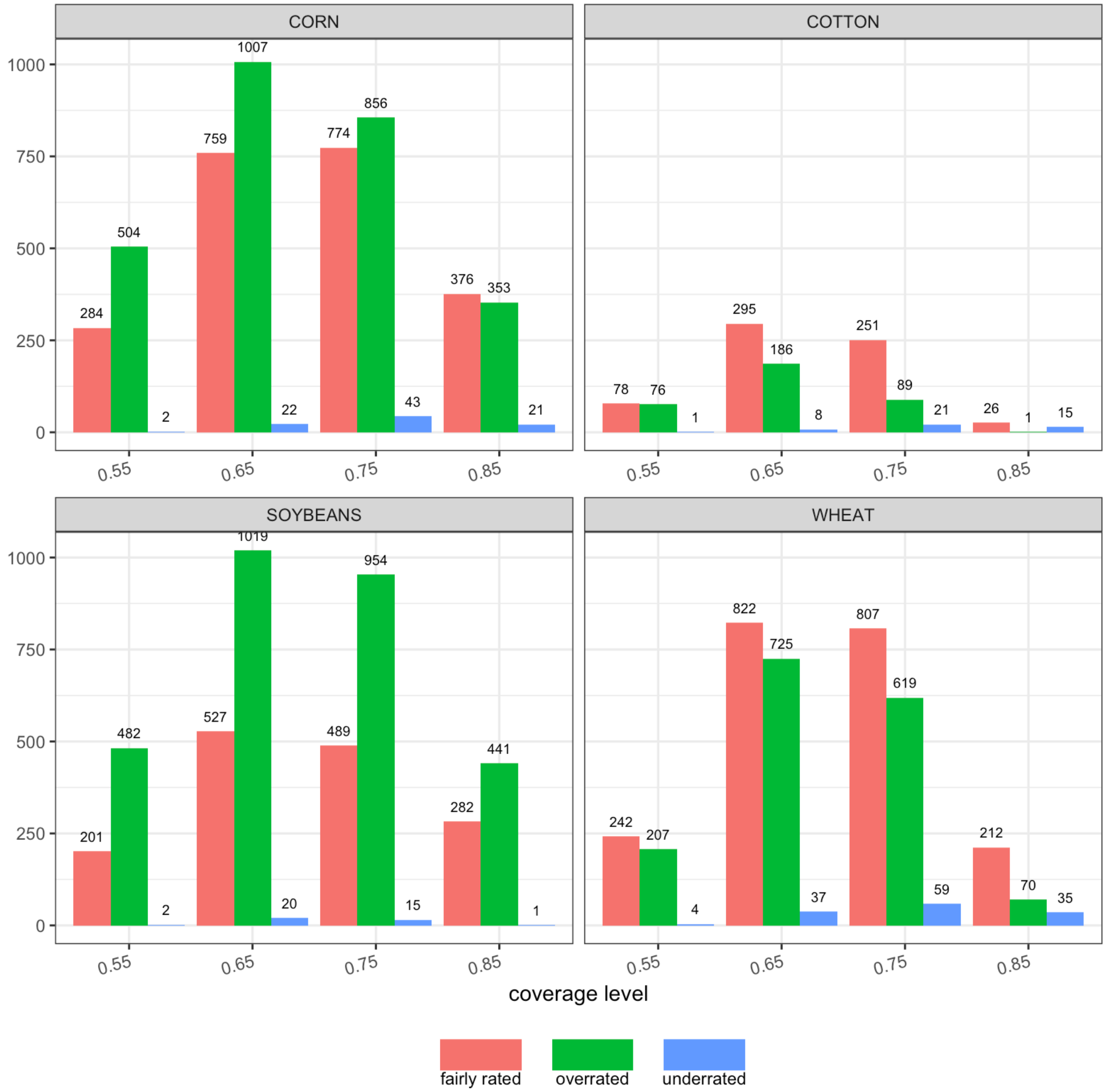


FIGURE 3.7 COUNTS OF MISRATING COUNTIES BASED ON SEGMENTED LOSS RATIOS

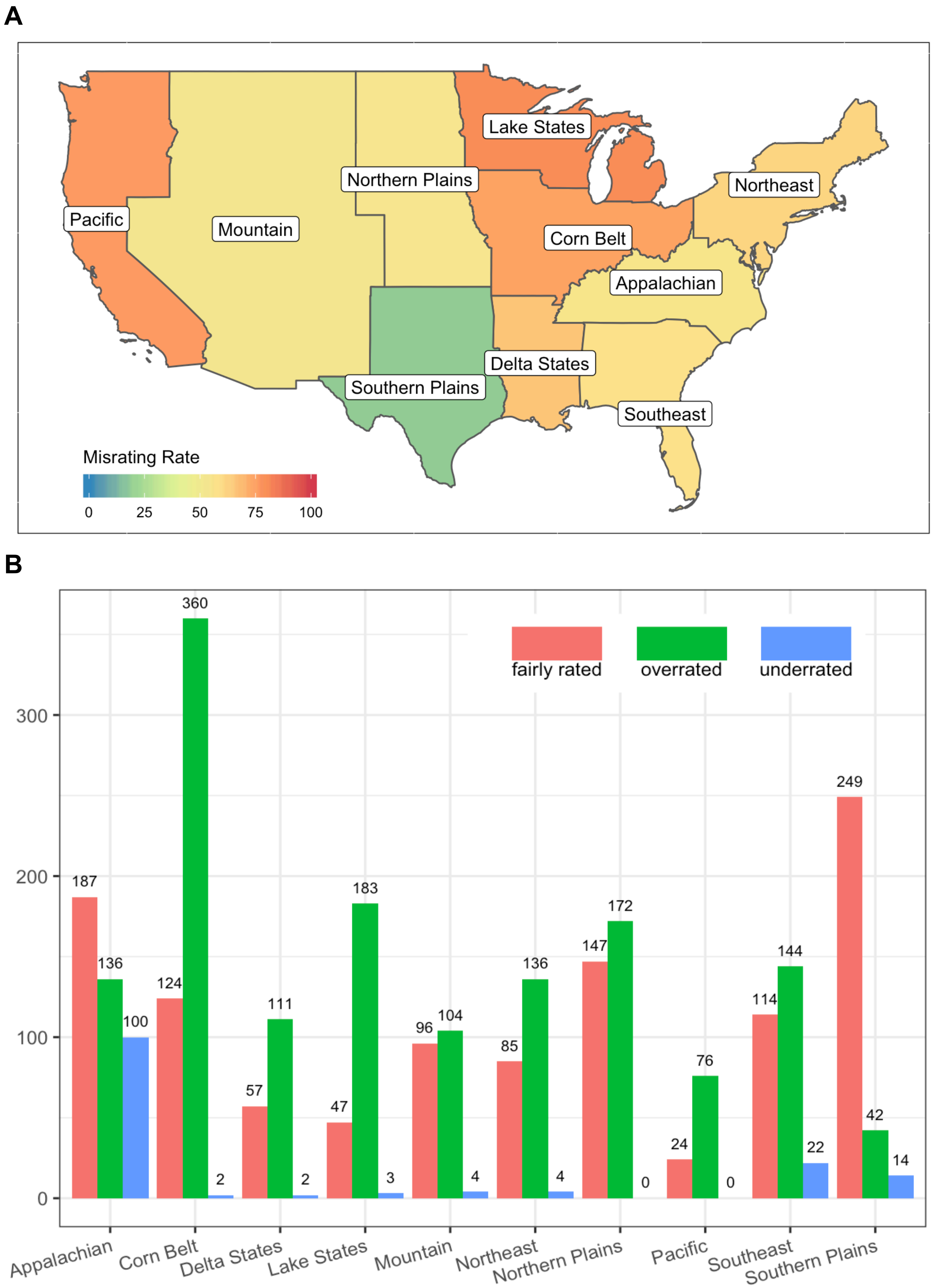


FIGURE 3.8 DISTRIBUTION OF MISRATING COUNTIES BY FARM PRODUCTION REGIONS

TABLE 3.1 RESULTS OF JOIN-COUNT TEST

	Join-count	Expected	Variance	z-value
Fairly_rated - Fairly_rated	2,037	1,387.65	494.49	29.20
Overrated - Overrated	3,129	2,268.37	550.90	36.67
Underrated - Underrated	180	25.21	21.29	33.55
Overrated - Fairly_rated	2,201	3,551.19	1,665.27	-33.10
Underrated - Fairly_rated	426	375.51	212.93	3.43
Underrated - Overrated	116	480.06	229.07	-24.05
Jtot	2,742	4,406.76	1,705.84	-40.31

References:

Annan, Francis, Jesse Tack, Ardian Harri, and Keith Coble. "Spatial pattern of yield distributions: implications for crop insurance." *American Journal of Agricultural Economics* 96, no. 1 (2013): 253-268.

Annan, Francis, and Wolfram Schlenker. "Federal crop insurance and the disincentive to adapt to extreme heat." *American Economic Review* 105, no. 5 (2015): 262-66.

Babcock, Bruce A., Chad E. Hart, and Dermot J. Hayes. "Actuarial fairness of crop insurance rates with constant rate relativities." *American Journal of Agricultural Economics* 86, no. 3 (2004): 563-575.

Botts, Ralph R., and James N. Boles. "Use of normal-curve theory in crop insurance ratemaking." *Journal of Farm Economics* 40, no. 3 (1958): 733-740.

Bivand, R.S., Pebesma, E.J., Gomez-Rubio, V. and Pebesma, E.J., *Applied spatial data analysis with R,* Springer, New York, 2008

Chen, Zhangliang and Sandy Dall'Erba. "Do crop insurance programs preclude their recipients from adapting to new climate conditions?". *REAL working paper 17-T-2* (2019).

Cliff, Andrew David, and J. Keith Ord. *Spatial processes: models & applications*. Taylor & Francis, 1981.

Coble, Keith H., Thomas O. Knight, Barry K. Goodwin, Mary Frances Miller, Roderick M. Rejesus, and George Duffield. "A comprehensive review of the rma aph and combo rating methodology: Final report." *Report prepared for the USDA Risk Management Agency by Sumaria Systems, Inc*., US Department of Agriculture, Risk Management Agency, Washington, DC (2010).

Coble, Keith H., and Thomas O. Knight. "Crop insurance as a tool for price and yield risk management." In *A Comprehensive Assessment of the Role of Risk in US Agriculture*, (2002) pp. 445-468. Springer US.

Crawley, Michael J. *Statistics: an introduction using R*, J. Wiley, Chichester, West Sussex, 2005.

Dalgaard, Peter. *Introductory Statistics with R*, Springer–Verlag, New York, 2002.

Dale, Mark RT, and Marie-Josée Fortin. *Spatial analysis: a guide for ecologists*. Cambridge University Press, 2014.

Dall'erba, Sandy and Francina Dominguez. "The Impact of Climate Change on Agriculture in the South-West United States: the Ricardian Approach Revisited", Spatial Economic Analysis, 11, no.1 (2016): 46-66

Epperson, Bryan K. "Covariances among join-count spatial autocorrelation measures." *Theoretical Population Biology* 64, no. 1 (2003): 81-87.

Farber, Steven, Manuel Ruiz Marin, and Antonio Páez. "Testing for spatial independence using similarity relations." *Geographical Analysis* 47, no. 2 (2015): 97-120.

Getis, A. and Ord, J.K., "The analysis of spatial association by use of distance statistics". *Geographical analysis* 24, no.3 (1992): 189-206.

Glauber, Joseph W. "Crop insurance reconsidered." *American Journal of Agricultural Economics* 86, no. 5 (2004): 1179-1195.

Goodwin, Barry K. "Premium rate determination in the federal crop insurance program: what do averages have to say about risk?" *Journal of Agricultural and Resource Economics* (1994): 382-395.

Goodwin, Barry K., and Ashley Hungerford. "Copula-based models of systemic risk in US agriculture: implications for crop insurance and reinsurance contracts." *American Journal of Agricultural Economics* 97, no. 3 (2014): 879-896.

Goodwin, Barry K., An empirical analysis of the demand for multiple peril crop insurance. *American Journal of Agricultural Economics*, 75, no.2 (1993), pp.425-434.

Goodwin, Barry K., and Vincent H. Smith. *The economics of crop insurance and disaster aid*. American Enterprise Institute. (1995)

Josephson, Gary R., Richard B. Lord, and Charles W. Mitchell. "Actuarial documentation of multiple peril crop insurance ratemaking procedures." *Report of Milliman and Robertson, Inc.* prepared for the Risk Management Agency (2000).

Ker, Alan P., and Barry K. Goodwin. "Nonparametric estimation of crop insurance rates revisited." *American Journal of Agricultural Economics* 82, no. 2 (2000): 463-478.

Lee, Youjin, and Elizabeth L. Ogburn. "Testing for Network and Spatial Autocorrelation." arXiv preprint arXiv:1710.03296 (2018).

Mankiw, N. Gregory. *Principle of Microeconomics*. Cengage Learning, 2016.

Noether, Gottfried E. *Introduction to statistics: the nonparametric way*. Springer Science & Business Media, 1991.

O'sullivan, David, and David Unwin. *Geographic information analysis*. John Wiley & Sons, 2014.

Plant, Richard E. *Spatial data analysis in ecology and agriculture using R* (2nd Edition). CRC Press, 2018.

Plastina, Alejandro, and William Edwards. "Proven Yields and Insurance Units for Crop Insurance." (2017). www.extension.iastate.edu/agdm

Ramirez, Octavio A. "Estimation and use of a multivariate parametric model for simulating heteroskedastic, correlated, non-normal random variables: the case of corn belt corn, soybean, and wheat yields." *American Journal of Agricultural Economics* 79, no. 1 (1997): 191-205.

Ramirez, Octavio A., Carlos E. Carpio, and Alba J. Collart. "Are the federal crop insurance subsidies equitably distributed? Evidence from a Monte Carlo simulation analysis." *Journal of agricultural and resource economics* (2015): 457-475.

Roberto Ezcurra, Belén Iraizoz, Pedro Pascual & Manuel Rapún. "Spatial disparities in the European agriculture: a regional analysis", Applied Economics, 40 no.13 (2008): 1669-1684

Sherrick, Bruce J., Fabio C. Zanini, Gary D. Schnitkey, and Scott H. Irwin. "Crop insurance valuation under alternative yield distributions." *American Journal of Agricultural Economics* 86, no. 2 (2004): 406-419.

Sherrick, Bruce, Gary D. Schnitkey, and Joshua D. Woodward. "Crop insurance loss experience, ratings changes, and impacts on participants." *Agricultural Finance Review* 74, no. 4 (2014): 443-463.

Shields, Dennis A. "Federal crop insurance: Background." Washington DC: US Congressional Research Service Report 40532. (2015a)

Shields, Dennis A. "Farm Safety Net Programs: Background and Issues." Washington DC: US Congressional Research Service Report 43758. (2015b)

Skees, Jerry R., and Michael R. Reed. "Rate making for farm-level crop insurance: implications for adverse selection." *American Journal of Agricultural Economics* 68, no. 3 (1986): 653-659.

Smith, Vincent H., and Barry K. Goodwin. "Private and public roles in providing agricultural insurance in the United States." *Public Insurance and Private Markets* (2010): 173-210.

Tolhurst, Tor N., and Alan P. Ker. "On technological change in crop yields." *American Journal of Agricultural Economics* 97, no. 1 (2014): 137-158.

U.S. Government Accountability Office. *CROP INSURANCE: Opportunities Exist to Improve Program Delivery and Reduce Costs.* GAO-17-501. Washington, DC, 2017. Accessed May 12, 2019. https://www.gao.gov/products/GAO-17-501

U.S. Government Accountability Office. *CROP INSURANCE: Considerations in Reducing Federal Premium Subsidies.* GAO-14-700. Washington, DC, 2014. Accessed May 12, 2019. http://www.gao.gov/products/GAO-14-700.

U.S. Government Accountability Office. CROP INSURANCE: *In Areas with Higher Crop Production Risks, Costs Are Greater, and Premiums May Not Cover Expected Losses*. GAO-15-215. Washington, DC, 2015. Accessed May 12, 2019. http://www.gao.gov/products/GAO-15-215.

U.S. Government Accountability Office. *CROP INSURANCE: Opportunities Exist to Improve Program Delivery and Reduce Costs*. GAO-17-501. Washington, DC, 2017. Accessed May 12, 2019. https://www.gao.gov/products/GAO-17-501.

Varian, Hal R. *Intermediate microeconomics with calculus: a modern approach.* WW Norton & Company, 2014.

Woodard, Joshua D. "Integrating high resolution soil data into federal crop insurance policy: Implications for policy and conservation." *Environmental Science & Policy* 66 (2016): 93-100.

Woodard, Joshua D., and Leslie J. Verteramo-Chiu. "Efficiency impacts of utilizing soil data in the pricing of the federal crop insurance program." *American Journal of Agricultural Economics* 99, no. 3 (2017): 757-772.

Woodard, Joshua D., Bruce J. Sherrick, and Gary D. Schnitkey. "Actuarial impacts of loss cost ratio ratemaking in US crop insurance programs." *Journal of Agricultural and Resource Economics* (2011): 211-228.

Woodard, Joshua D., Gary D. Schnitkey, Bruce J. Sherrick, Nancy Lozano-Gracia, and Luc Anselin. "A spatial econometric analysis of loss experience in the US crop insurance program." *Journal of Risk and Insurance* 79, no. 1 (2012): 261-286.

Yeh, Martin H., and Roland Y. Wu. "Premium Ratemaking in an All Risk Crop Insurance Program." *Journal of Farm Economics* 48, no. 5 (1966): 1580-1586.

Zhu, Ying, Barry K. Goodwin, and Sujit K. Ghosh. "Modeling yield risk under technological change: Dynamic yield distributions and the US crop insurance program." *Journal of Agricultural and Resource Economics* (2011): 192-210

Zulauf, C. "Why Crop Insurance Has Become an Issue." *farmdoc daily* (6):76, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, April 20, 2016.

CONCLUSIONS

The three stand-alone but closely-related chapters in this dissertation confirm the complexity and difficulty of actually estimating the impact of man-made climate change on the agricultural sector as multiple forces, both from market and government, affects farmers' profit and their willingness to pay for self-adaptation activities towards adverse changes in local climate. Well-designed policies allow market forces to function, which could mitigate the negative impacts of climate change, encourage adaptation behavior, and reduce fiscal burden. Poorly-designed policies, on the other hand, distort the free market outcome in the cost of exacerbating adverse climate effects, demoralize farmers from taking active adaptation, and wasting taxpayers' money. In particular:

Chapter 1 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.

Chapter 2 demonstrates that federal crop insurance programs reduce significantly or even cancel out the farmers' willingness to adapt. We start by extending the traditional Ricardian setting to reflect that profit-maximizing farmers take their production decisions based on the certainty that paying an insurance premium guarantees they will receive support benefits in the case of a bad harvest. Results indicate that the crop insurance programs can heavily distort the farmers' incentive to adapt to new local climate conditions whether they represent continuous events, such as degree days, or more extreme events such as the probability of a drought.

Chapter 3 documents the scale, pattern and fiscal implications of misrating the premium in the federal crop insurance program. By collecting over 2 million actuarial records from USDA's Risk Management Agency and applying a formal statistical approach, our results confirm the significant prevalence of misrating in the distribution of insurance programs across all crops as well as for the four major crops (corn, soybean, wheat, cotton). Furthermore, we detect the significant presence of positive spatial autocorrelation in the counties' misrating status ("overrated" and "underrated") which indicates regional clusters of loss experience and that the boundaries of a group of counties, rather than of each specific county, may be more appropriate to define a premium. Last but not least, the paper offers a model suggesting that reducing the total outlay of the crop insurance is feasible only under certain elasticity conditions.