Do crop insurance programs preclude their recipients from adapting to new climate conditions?

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Abstract: This paper studies the potential impacts of federal crop insurance programs on farmers' adaptation towards climate warming. With a Ricardian framework incorporating crop insurance, we demonstrate how crop insurance reduces the sensitivity of farmers' land value - the discounted sum of future profit - to changes in climate conditions. A modified Ricardian regression using the dataset of U.S. counties verifies that the climate variables are more likely to have smaller and less significant marginal effects on farmland value in those counties being the major beneficiary of crop insurance programs.

Keywords: climate change, crop insurance, Ricardian approach

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1. Introduction

The enactment of the Crop Insurance Reform Act of 1994 paved the way for crop insurance to become the main pillar of current U.S. farm subsidy system. It costs American tax payer around seven billion dollars each year and accounts for roughly 30 to 40% of the annual total agricultural subsidies budget since 2010 according to the Environmental Working Group's farm subsidy database. The Agricultural Act of 2014 confirms Congress's attempt to keep expanding crop insurance programs to replace the direct payment programs, which might enhance its importance in U.S. agricultural policy system even further in the near future.

As agricultural economics literature has well documented, crop insurance can distort farmers' production decisions, such as land allocation, the choice of crop mix, optimal amounts of input use and infrastructural investment (Goodwin and Smith, 1995; Knight and Coble, 1997; Coble and Knight, 2002). More recently, the literature has decried crop insurance programs for their side effects on climate change adaptation. For instance, Burke and Emerick (2015) highlight that they discourage U.S. farmers from being actively engaged in adaptation activities such as optimizing crop mix and improving irrigation systems. Indeed, these programs act as a moral hazard since farmers are aware that the government will compensate a large proportion of the actual damages caused by climate change. Anna and Schlenker (2015) provide an empirical evidence for such potential distortion effect under the crop production framework.

Our contribution consists in demonstrating that crop insurance programs distort the relationship between climate variables and farmland value, the relationship of interest in a Ricardian framework (Mendelsohn et al., 1994; Schlenker et al., 2005; Schlenker et al, 2006; Deschênes and Greenstone, 2007). Our estimation strategy consists in, first, separating the farmers into two groups based on the net financial benefit they receive from crop insurance and, second, testing whether the marginal effect of the climate data differs significantly across groups. We identify the net recipient farmers as those who regularly receive a compensation that is larger than their annual payment. The other group of farmers corresponds to the actuarially-fair participants as their expected indemnity is equal to or slightly less than the premium they pay. Our conceptual model predicts that the sensitivity of the expected profit to changes in climate is lesser in the net recipient group than in the actuarially-fair group. The more a farmer relies on indemnity to compensate for his loss, the less his ex-post profit reflects his actual production conditions. The same reasoning holds true for land value, the dependent variable traditionally used in a Ricardian framework, since it represents the discounted sum of future profits.

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 with structural instability in the form of the two groups discussed earlier. Our regression results highlight the significant difference between groups and that, in the net recipient group, the magnitude and precision of the marginal effect of the climate variables are biased toward zero compared to the actuarially-fair group. 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) that highlights how overall subsidies have a small positive effect on land 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 failed to address. Finally, Dall'erba and Dominguez (2016) focus on the South-Western part of the

U.S and, like Polsky (2004), they conclude to a small but significant positive effect of the subsidies. Their article is the only one among the three to control for the endogeneity of the subsidy payments by two-stage-least-square.

This manuscript distinguishes itself from the previous literature for three reasons. First, instead of pooling all forms of subsidies together, singling out crop insurance allows us to formally incorporate it into the Ricardian framework, generate testable hypotheses regarding its impacts based on the behavioral model. Second, our approach enable us to direct measure the impact of crop insurance on marginal effects of climate variables whereas previous work use subsidies as just another control variable. That specification only allows subsidies affect those marginal effects indirectly. 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 compared to the crop production approach that, by design, rules out some forms of adaptation such as land use changes.[2]

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 manuscript is based on the loss ratio which is defined as indemnity payments divided by the total premium. It represents the net benefit (or loss) farmers take from the program, which identifies the farmers' desire to adapt to new climate conditions more precisely than the participation rate. Indeed, the latter 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

[2] However, one should not exaggerate this point by saying that crop production framework rules out any types of adaptation. Miao et al. (2016) offer an indirect evidence of the potential for adaptation still takes place when showing that crop yields respond to market price changes, which suggests that as crop prices increase due to adverse climatic conditions in the future, farmers are likely to respond by changing production practices and increasing yields.

exacerbates the loss of corn and soybean yield caused by extreme degree-days[3]. 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 paper continues with an extension of the Ricardian framework. It shows that the response of land values to new climate conditions depends on whether the farmers are net crop insurance recipients or actuarially-fair participants. 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. Conceptual Framework

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/her 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:

$$(1) \qquad \pi_i = \max_{j \in J}\left\{p_j f_j\left[\mathbf{x}_{ij}\left(p_j, \mathbf{w}, c_i, \theta_i\right); c_i, \theta_i\right] - \mathbf{w} \cdot \mathbf{x}_{ij}\left(p_j, \mathbf{w}, c_i, \theta_i\right) + \varepsilon_{ij}\right\} - R_i$$

[3] Extreme degree-days are defined as the degree-days above certain harmful heat thresholds to crop growth. Annan and Schlenker (2015) set the thresholds based on those empirically discovered 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* ($\mathrm{p_j}$) times its output $\mathrm{f_j}[\cdot]$. We denote the production function of activity *j* as a function of input $\mathbf{x}_{\mathrm{ij}}$ and two groups of parameters, namely the climatic parameters $\mathrm{c_i}$ 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 $\mathbf{x}_{\mathrm{ij}}$. 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: $\mathbf{x}_{\mathrm{ij}}\left(\mathrm{p_j}, \mathbf{w}, \mathrm{c_i}, \theta_{\mathrm{i}}\right) \equiv \mathrm{argmax}\,\{\mathrm{p_j f_j}\left[\mathbf{x}_{\mathrm{ij}}, \mathrm{c_i}, \theta_{\mathrm{i}}\right] - \mathbf{w} \cdot \mathbf{x}_{\mathrm{ij}}\}$. The term $\varepsilon_{\mathrm{ij}}$ 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, $\mathrm{R_i}$ is a fixed cost that corresponds to the land rent the farmer pays to the landlord.

In a long run equilibrium where farmers freely enter or leave the market, the expected profit should be zero. By setting $\mathbb{E}(\pi_{\mathrm{it}}) = 0$, Eq. (1) implies:

$$\mathrm{R_i} = \mathrm{p_{j^*} f_{j^*}}\left[\mathbf{x}_{\mathrm{ij^*}}, \mathrm{c_i}, \theta_{\mathrm{i}}\right] - \mathbf{w} \cdot \mathbf{x}_{\mathrm{ij^*}} \tag{2}$$

Where j^* denotes the optimal use of land *i* and where the arguments of the optimal input use function $\mathbf{x}_{\mathrm{ij^*}}(\cdot)$ are suppressed for simplicity. Eq. (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:

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

Where *r* is the discount rate. Eq. (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 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 premium rate S and the associated protected net 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 protected level M, the farmer will receive the difference through an indemnity payment. The long-run equilibrium agricultural profit with crop insurance is therefore:

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

It is worth noting that, compared to Eq. (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}. To highlight this point, we should consider the net revenue for the optimal activity j with crop insurance:

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

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

$$\text{(5)} \quad \mathbb{E}[\pi_{ij}] = \{p_j f_j[\mathbf{x}_{ij}, c_I, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij} - S_{ij}\} \cdot (d_{ij}) + \{M_{ij} - S_{ij}\} \cdot (1 - d_{ij}) - R_i$$

Again, the zero-profit assumption implies that:

$$\text{(6)} \quad R_i^{cp} = \{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij}\} \cdot (d_{ij}) + \{M_{ij}\} \cdot (1 - d_{ij}) - S_{ij}$$

The associated land value is

$$\text{(7)} \quad V_i^{cp} = \left(\frac{1+r}{r}\right)\left\{\{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij} + \hat{\varepsilon}_{ij}\} \cdot (d_{ij}) + \{M_{ij}\} \cdot (1 - d_{ij})\right\}$$

Taking the partial derivative of Eq. (7) with respect to the climate variable c_i, we get the marginal effect of climate on farmland value in the case of crop insurance.

$$\text{(8)} \quad \frac{\partial V_i^{cp}}{\partial c_i} = (d_{ij}) \cdot \underbrace{\left\{\left(\frac{1+r}{r}\right)\frac{\partial}{\partial c_i}\{p_j f_j[\mathbf{x}_{ij}, c_i, \theta_i] - \mathbf{w} \cdot \mathbf{x}_{ij}\}\right\}}_{=\frac{\partial V_i}{\partial c_i}} < \frac{\partial V_i}{\partial c_i}$$

The term in the braces is the marginal effect of climate without crop insurance. We can verify it by taking the derivatives of Eq. (3) with respect to c_i. The inequality in Eq. (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.

Furthermore, Eq. (8) implies that the extent of this attenuation effect depends on $(1 - d_{ij})$, i.e. the probability that loss occurs. The more likely a farmer suffers from a loss and receives indemnity, the less his land value responds to changes in climate. This observation motivates us to split the sample between the farmers who have a high probability to receive an indemnity (henceforth the net recipients) and those who have a low one (henceforth the actuarially-fair participants). Our conceptual model predicts that a smaller marginal effect of the climate variables should be found among the net recipients.

Finally, the Ricardian framework is essentially a hedonic method. Rosen (1974)'s classic interpretation of the hedonic equilibrium allows us to further infer the disincentive effect of crop insurance on farmers' adaptation activities. According to Rosen, the marginal effect of the climate variables can be interpreted as farmers' willingness to pay/accept for a favorable/unfavorable climate condition. Crop insurance reduces marginal effects, therefore lowers farmers' willingness to pay for a better climate. And less willingness to pay indicates the less willingness to adapt to adverse changes in the future climate.

2.3 An illustrative example with only two feasible activities

[Insert figure 1 here]

Figure 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 chose, 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 details 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 is that it is a better revenue outcome than B^{short} where the farmer has not adapted to new climate conditions.

Panel (b) assumes the similar climate change scenario but with 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 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/her original insurance policy remains unchanged. In addition, the introduction of crop insurance alters the Ricardian reasoning behind Panel (a) in two profound ways. First, since crop insurance prevents the farmer's ex-post net revenue from dropping below the protected level, he/she 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 outer envelope highlighted by a bold line that defines the hedonic equilibrium. This alteration of the hedonic curve corresponds to the diminished marginal effect of climate, as shown in our algebraic model.

Panel (c) illustrates the attenuation effect using a truncated data analogy. The solid line is the regression line when we can observe the actual net revenue for all observations. The dashed line, on the other hand, is the regression line when several observations are truncated by the protected revenue set by the crop insurance programs. The dashed line is clearly flatter than the solid one, which means the marginal effects decrease with the presence of crop insurance.

Before we move to the empirical section, we need to note two important points. First, the support revenue and premium rate are usually based on the applicants' historical planting records. Everything else being equal, farmers who have longer historical records of planting a specific crop are more likely to get better policy terms than those who have never planted it. As a result, crop rotation or the introduction of a new crop is not necessarily in the farmer's best interest and adaptation through these means is hindered. Second, our simple model assumes that farmers pay the entirety of the policy premium by themselves. In reality, the introduction of the 1994 Crop Insurance Reform Act has encouraged participation by subsidizing the purchase of the premium rate. The average share of premium paid by farmers has dropped from 74% in 1994 to 38% in 2014 (Zulauf, 2016). As a result, the actual subsidies associated with crop insurance can be theoretically divided into two categories. One is used to finance the extra indemnity payment and the other one supports the premium. Unlike the former one, premium support does not distort the farmers' decision to mix crops given that the premium support discounts are the same across crops, which is consistent with the current crop insurance practices in United States. Therefore, including subsidies for the purchase of the premium does not change the main results of our analysis.

3 Empirical Model

Empirical estimation of whether crop insurance programs reduce the sensitivity of farmland values to local climate conditions is not trivial. Such programs are determined by a set of endogenous factors such as a farm's and its peers' past revenues[4] which do not satisfy the usual normality conditions. While Dall'erba and Dominguez (2015) have used an instrumental variable approach to provide unbiased and efficient estimates of these programs, we prefer to follow the theoretical framework above by identifying the marginal effects of various climate conditions on land value across the group of actuarially fair participants and the one

[4] See Shields (2015) for more details on the criteria used to design crop insurance policies.

of the net recipients. We expect their difference to be statistically significant and climate to play a lesser role in the net recipient group.

3.1 Data sources and processing issues

Our estimation strategy 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) setting the urban county threshold at 400 inhabitants per square mile. As a result, our final sample is composed of 2,813 rural counties.

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) a set of socioeconomic control variables namely population density, personal income per capita, irrigation ratio and fertilizer expenditure; and (3) nine soil quality control variables commonly used in the literature. Their description appears below.

Climate Normal --- Our climate data come from the National Centers of Environmental Protection’s the North American Regional Reanalysis (NARR) product (Mesinger *et al*. 2006). 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 Mendelsohn *et al.* (1994) and Schlenker *et al.* (2006), we decide to work with the four-season mean temperature and 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.

Extreme Weather Event --- As it is well-known that a changing climate is expected to increase the frequency and intensity of extreme weather events, we investigate their importance by defining droughts and wet spells on the Palmer Drought Severity Index (PDSI). PDSI measures the standard deviation of a given month's rainfall from its historical average. Its value ranges from +6 to -6 whereby a negative PDSI means the current precipitation is less than its historical average and corresponds to a drought. Therefore, we count a month as drought month if the monthly PDSI is between [-3, -6]. Similarly, a wet spell month is one for which PDSI is between [3, 6]. Then, we calculate the proportion of time a county was under either a drought or a wet spell over our 20-year period and call it their respective probability of occurrence.

Crop Insurance --- The crop insurance data come from the Summary of Business (SOB) of USDA's Risk Management Agency (RMA). SOB includes county-level information of crop insurance practices over 1980-2015. The raw data contains the total number of farmers that contract a policy, the premium they pay, how many of them report a loss and receive indemnity payments. This paper uses the loss ratio data reported in SOB to identify the counties heavily affected by the crop insurance policy. We aggregate the raw data by agricultural activity types, insurance plan and coverage category to a county average.

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. We also capture the heterogeneity present across local production processes and land use patterns by complementing our set of regressors with fertilizer expenditure per acre, the ratio of irrigated farmland to total farmland, a county's share of cropland, the share of corn and soybean in farmland. All data come from USDA's censuses. 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 (STATASGO2) National Resource Inventory. 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.

3.2 Criteria to identify the net recipients

We use the 20-year average of the ratio between indemnity payment and the total premium. In the theoretical model, we defined the actuarially-fair participants of crop insurance as the farmers for whom the expected indemnity payment is equal to the annual premium. It means that their long-run average loss ratio is equal to one while it is greater than one for the net recipients.

According to the law of large numbers, the mean of a random sample converges to its expectation. Therefore, we identify the members of the two groups above based on where each county stands with regards to the 20-year average loss ratio. Figure 2 Panel (a) is the histogram with the kernel density plot of the 20-year average loss ratio. It shows that the mean is around one (0.971), which means the majority of the counties can be categorized as actuarially-fair. The right tail of the distribution, on the other hand, depicts the counties for whom the 20-year average loss ratio is above one. Among those, we isolate the counties with a loss ratio above 90% of the distribution and call them the net recipients. This selection process is based on the *intensity* of the crop insurance programs.

One potential pitfall of this approach is that a county might be mistakenly identified as a net recipient merely because it received a large amount of indemnity payment over one or a small number of years. We want to exclude these counties from the net recipient group since, according to the theory, the net recipients should have a larger-than-one loss ratio on a regular basis. Hence, we complement the previous approach with a selection based on the *frequency* of experiencing a loss ratio greater than one over the 20-year period of interest. Figure 2 Panel (b) is the histogram with the kernel density plot of this frequency. Like for the intensity criteria, we set the one-sided 10% rejection rule to detect the outliers who have frequently received indemnity payments above the total premium.[5]

3.3 Summary statistics

Before setting up the regression model, we compare in Table 1 the summary statistics of the two groups. Results indicate that the sample mean of farmland value is almost the same across groups at around $ 3,000 per acre. The groups experience also very similar climate normals. The differences in the four season temperature

[5] For robustness checks, we moved the intensity and frequency criteria from its default 10% threshold to the 5% and 15% thresholds. Our main regression results remained unchanged. Complete results available from the authors upon request.

and precipitation are less than 7%, except for the winter temperature which is 13% warmer in the net recipient group. Comparing the probability of extreme events reveals a surprising result also. The net recipient counties do *not* experience a higher probability of extreme weather events as the common wisdom would suggest. In fact, they have a lower probability of being hit by both droughts and wet spells. We also find that the two groups diverge in terms of production characteristics. In the net recipient group, the farmers spend on average 60% less on fertilizer, and they also have 20% less land under irrigation. This last observation suggests that crop insurance may discourage farmers from undertaking appropriate adaptation activities. Indeed, previous studies on agricultural adaptation to climate change (Howden et al., 2007; Antel and Capalbo, 2010; Hertel and Lobell, 2014) suggest that an increasing use of fertilizer and of irrigation are two common adaptation strategies to a warmer climate that farmers can start by themselves.

[Insert table 1 here]

3.4 Model specification choices

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

$$\begin{aligned}\mathbf{y_{ijt}} = {} & \overline{\mathrm{T}}_{\mathbf{ij}}'\delta_1 + \overline{\mathrm{T}}_{\mathbf{ij}}^{\mathbf{2}\,\prime}\delta_2 + \left(\overline{\mathrm{T}}_{\mathbf{ij}}' \times \mathbf{NR_{ij}}\right)\gamma_1 + \left(\overline{\mathrm{T}}_{\mathbf{ij}}^{\mathbf{2}\,\prime} \times \mathbf{NR_{ij}}\right)\gamma_2 \\ & + \mathrm{X}_{\mathbf{ijt}}\beta + \mathrm{Z}_{\mathbf{ij}}\alpha + \boldsymbol{\eta}_{\mathbf{j}} + \boldsymbol{\lambda}_{\mathbf{t}} + \boldsymbol{\xi}_{\mathbf{jt}} + \boldsymbol{\epsilon}_{\mathbf{ijt}} \qquad \boldsymbol{\epsilon}_{\mathbf{ijt}} \sim \mathbf{N}(\mathbf{0}, \boldsymbol{\sigma}_{\boldsymbol{\epsilon}}^{\mathbf{2}})\end{aligned} \tag{9}$$

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. **X** is a matrix of time-variant socioeconomic controls while **Z** captures all the time-invariant soil quality variables.

Our model introduces a structural change through the binary variable *NR*. It is a dummy variable that identifies the net recipient counties. The coefficients ($\boldsymbol{\gamma}$) associated to the interaction between *NR* and the climate variables $\mathbf{T}$ captures the difference in the marginal effects of these variables on farmland value between the actuarially fair counties and the net recipient counties. Significant $\boldsymbol{\gamma}$s would indicate that farmland values of the two groups respond to local climate conditions differently. Furthermore, we can compare the sign of the marginal effects $\boldsymbol{\delta}$ with that of $\boldsymbol{\gamma}$. If they are different, then the net recipient counties are less sensitive to changes in climate conditions than the actuarially fair counties, which supports our hypothesis that crop insurance programs dampen adaptation to climate change. Last but not least, η_j are state fixed effects, λ_t are year fixed effects and ξ_{jt} are year-by-state fixed effects. Since Schlenker *et al.* (2006) and Deschênes and Greenstone (2007), adding spatial and temporal fixed effects has become a standard practice aiming at controlling for the unobservable factors that might confound the marginal effect of climate. While the year fixed effects picks up the time trend, such as changes in commodity prices, technological innovations and policy shocks that are common to the entire country, state fixed effects do the same but for each individual state. Finally, year-by-state fixed effects capture time trends that are common to the counties of the same state and which might be generated by local business cycles and local 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. (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. We employ two commonly used techniques to remedy this issue: (1) clustering the error terms at the county level as suggested by

Deschênes and Greenstone (2007); and (2) using the spatial panel data HAC estimator of Conley (2008).

4 Results

4.1 The baseline regression results

We use Eq. (9) as the main model specification of this paper and its estimation results are reported in Table 2. All the variables listed in Section 3.1 and the fixed effects described in Section 3.4 are included as regressors. We suppress the estimates of soil quality controls, socioeconomic conditions, squared terms of climate variables and fixed effects for clarity purposes[6].

[Insert table 2 here]

The first three columns of Table 2 report the regression results of Eq. (9) when the net recipient counties are selected based on the intensity criterion. Column (1) reports the marginal effects of the climate variables in the actuarially-fair group, i.e. $\boldsymbol{\delta}$ in Eq. (9). Column (2) displays the coefficient estimates of the difference between the marginal effects of the actuarially-fair and the net recipient groups, i.e. $\boldsymbol{\gamma}$. Column (3) reports the marginal effects in the net recipient group, i.e. $\boldsymbol{\delta} + \boldsymbol{\gamma}$. The standard errors in that column are computed by the delta method.

Our theoretical framework suggests the followings: (i) $\boldsymbol{\gamma}$ should be statistical significant. (ii) $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ should have opposite signs; hence $\boldsymbol{\delta} + \boldsymbol{\gamma}$ converges to zero and, in some cases, becomes not significantly different from zero. Panel A presents the results for the seasonal average temperature. To a large extent, they confirm our expectations. First, we find that the climate variables affect farmland value differently across the two groups. Second, the estimates in Column (2) cancel out the significant coefficients found in Column (1) so that the marginal effect of

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

temperature in the net recipient counties is not significant, except for summer. Even for the latter, the reduction in the magnitude of the marginal effect is large at nearly 45%.

Panel B presents the results for precipitation. As in *Panel A*, we find a structural difference between the two groups. Comparing the results in columns (1) and (3), we find that during the growing seasons rainfall follows a pattern similar to temperature in that the marginal effect in the net recipient group is attenuated towards zero as it is in the opposite direction compared to the actuarially fair group. We also find that winter and autumn rainfall has a significant role in the net recipient group only. The importance of precipitation, to a large extent, depends on the existing irrigation infrastructures as Schlenker *et al.* (2005) pointed out. The irrigation system enables farmers to reallocate water resources over space and time. Therefore, the better irrigation system a region has, the less its agriculture relies on unpredictable local precipitation. The significantly positive impacts of winter and fall precipitation in the net recipient counties can also be interpreted as an evidence that these counties have a less developed irrigation infrastructure, as shown in table 1. It might also be caused by the fact that crop insurance precludes its net recipients from investing in irrigation system construction.

Panel C of the table reports the results associated with extreme weather events. As expected, column (1) shows the negative impacts of an increase in the probability of both drought and wet spell in the actuarially-fair group, although only the former is statistically significant. Neither of the two extreme weather events affects the net recipient group significantly, which confirms the predictions of our theoretical model.

Finally, Columns (4) to (6) presents the regression results when the frequency criteria is used to identify the net recipient counties. The main results are similar to those based on the intensity criteria. Indeed, we find again that the marginal effect of the climate variables in the net recipients is either attenuated and/or lose statistical significance compared to the actuarially-fair group. For instance, both spring temperature and rainfall have a positive impact in the actuarially-fair group, a result that is consistent with the knowledge of crop development. However, both of these positive impacts disappear in the net recipient group. Another evidence is the negative role of the probability of a drought that becomes non-significant in the net recipient group.

4.2 Structural difference between rainfed and irrigated counties

Previous Ricardian studies, namely Mendelsohn and Dinar (2003), Schlenker *et al.* (2005), Deschênes and Greenstone (2007) highlighted the structural difference between rainfed and irrigated counties in terms of the marginal effects of climate variables on land value. We include this form of heterogeneity to our Ricardian model in this subsection and check if this structural difference alters our main conclusions. A dummy variable (IR) is constructed to identify the irrigated status of the counties based on the ratio of the irrigated farmland to total farmland in 1997. Irrigated counties are countries with an irrigated ratio above 30%[7]. Interacting the irrigation dummy with climate covariates extends Eq. (9) as follows:

$$\begin{aligned} \mathrm{y}_{\mathrm{ijt}} = {} & \overline{\mathbf{T}}_{\mathrm{ij}}'\boldsymbol{\delta}_{\mathbf{1}} + \overline{\mathbf{T}}_{\mathrm{ij}}^{2\prime}\boldsymbol{\delta}_{\mathbf{2}} + \left(\overline{\mathbf{T}}_{\mathrm{ij}}' \times \mathrm{NR}_{\mathrm{ij}}\right)\boldsymbol{\gamma}_{\mathbf{1}} + \left(\overline{\mathbf{T}}_{\mathrm{ij}}^{2\prime} \times \mathrm{NR}_{\mathrm{ij}}\right)\boldsymbol{\gamma}_{\mathbf{2}} \\ & + \left(\overline{\mathbf{T}}_{\mathrm{ij}}' \times \mathrm{IR}_{\mathrm{ij}}\right)\boldsymbol{\zeta}_{\mathbf{1}} + \left(\overline{\mathbf{T}}_{\mathrm{ij}}^{2\prime} \times \mathrm{IR}_{\mathrm{ij}}\right)\boldsymbol{\zeta}_{\mathbf{2}} \\ & + \left(\overline{\mathbf{T}}_{\mathrm{ij}}' \times \mathrm{IR}_{\mathrm{ij}} \times \mathrm{NR}_{\mathrm{ij}}\right)\boldsymbol{\tau}_{\mathbf{1}} + \left(\overline{\mathbf{T}}_{\mathrm{ij}}^{2\prime} \times \mathrm{IR}_{\mathrm{ij}} \times \mathrm{NR}_{\mathrm{ij}}\right)\boldsymbol{\tau}_{\mathbf{2}} \\ & + \mathbf{X}_{\mathrm{ijt}} + \mathbf{Z}_{\mathrm{ij}}\boldsymbol{\alpha} + \eta_{\mathrm{j}} + \lambda_{\mathrm{t}} + \xi_{\mathrm{jt}} + \epsilon_{\mathrm{ijt}} \qquad \epsilon_{\mathrm{ijt}} \sim \mathrm{N}(0, \sigma_{\epsilon}^2) \end{aligned} \tag{10}$$

The irrigation status dummy (IR) along with the net recipient dummy (NR) partition the sample into four subgroups: (1) rainfed actuarially-fair counties (i.e.

[7] We choose 30% as the cutoff because it corresponds roughly to the 90% quantile of the distribution of the irrigated ratio in 1997. Several different cutoffs have been chosen by previous researchers, such as 20% by Schlenker *et al.* (2005), 10% by Deschênes and Greenstone (2007), so we use them as robustness checks. Our main results remain unchanged.

IR = 0 and NR = 0); (2) rainfed net recipient counties (i.e. IR = 0 and NR = 1); (3) irrigated actuarially-fair counties (i.e. IR = 1 and NR = 0); and (4) irrigated net recipient counties (i.e. IR = 1 and NR = 1).

Table 3 reports the regression results of Eq. (10). For the purpose of clarity, we choose to directly report the marginal effects of the climate variables. For the other subgroups except the reference one, the standard error of the estimates of marginal effect is calculated based on the delta method.

[Insert table 3 here]

To a large extent, the comparison between actuarially-fair and net recipient counties in both rainfed and irrigated groups confirm the baseline results. We first focus on the columns (1) and (2) that illustrate the comparison in the rainfed group. For almost every season, the marginal effects of seasonal temperature in the net recipient countries decrease in magnitude and statistical significance, which is consistent with our baseline results. Our findings for seasonal rainfall and extreme weather events are also similar as the baseline results. Columns (3) and (4) display the results for the irrigated group. Again, we find that the net recipient counties are more likely to display smaller and insignificant marginal effects of the climate variables, a pattern both predicted by our conceptual model and verified by the baseline regression results.

5 Conclusion

This paper challenges the climate change adaptation assumption embedded in the Ricardian framework by demonstrating that federal crop insurance programs significantly reduce or even cancel 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 a net recipient of crop insurance programs has little to no incentive to adapt to new local climate conditions. The model is then tested empirically and confirms our expectations. Based on a panel dataset covering all the continental U.S. counties and the four most recent censuses of USDA, we find that compared to their counterparts in the actuarially-fair group, farmland values in the net recipient group are less sensitive to changes in climate conditions.

The climate adaptation reduction effect induced by crop insurance programs might cause considerable social welfare loss in the long run. Under the current crop insurance system, all participants receive some federal support to finance part of their annual premium payment. In addition, the government subsidizes the net recipients through indemnity payments that have been the focus of this manuscript. Ultimately, if the policy makers aim at minimizing the potential damage of climate change on the U.S. agriculture, crop insurance programs should only function as a social safety net in the short run. 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. (Kandlikar and Risbey, 2000; Smit and Skinner, 2002; Mendelsohn, 2006; Howden et al., 2007; Zilberman et al., 2012; Hertel and Lobell, 2014)

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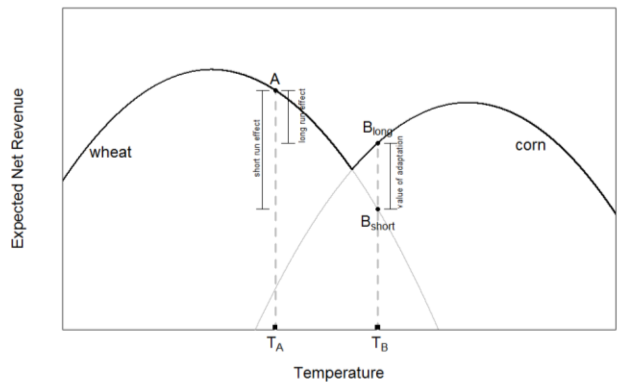
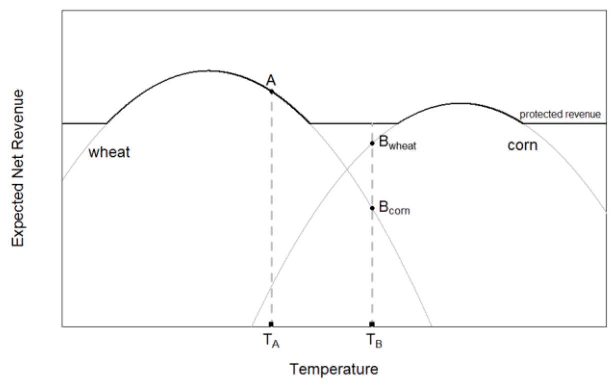
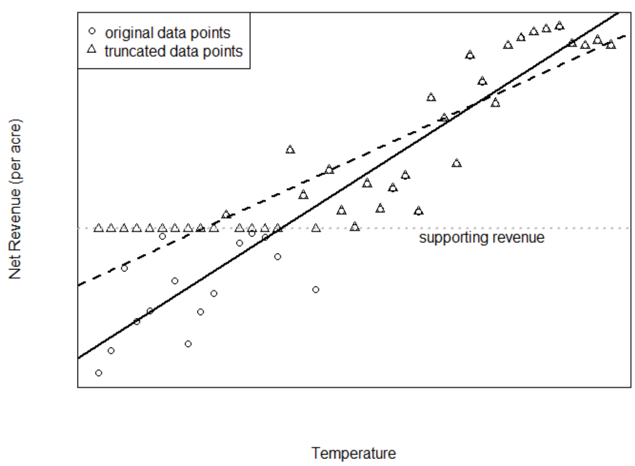


Panel (a) Standard Ricardian Approach Plot

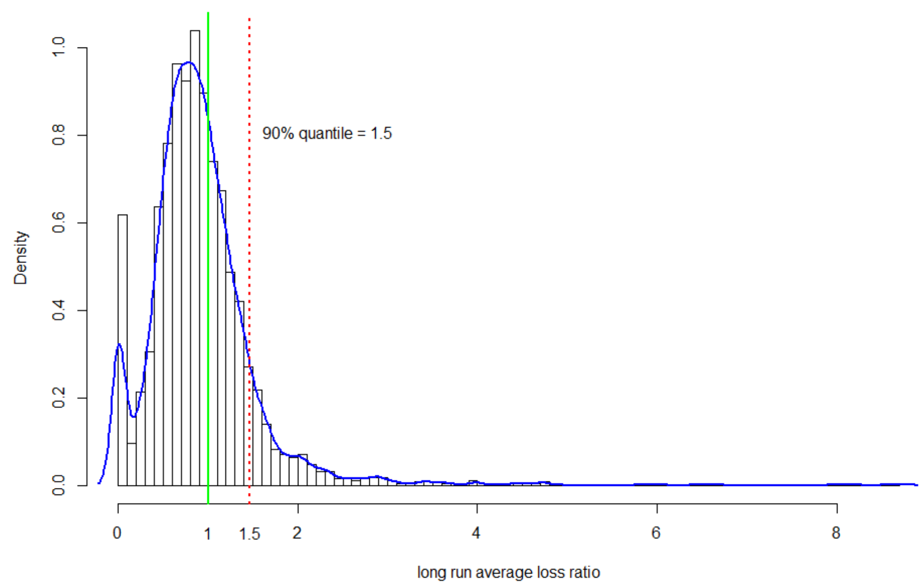


Panel (b) Ricardian Plot with Protected Revenue

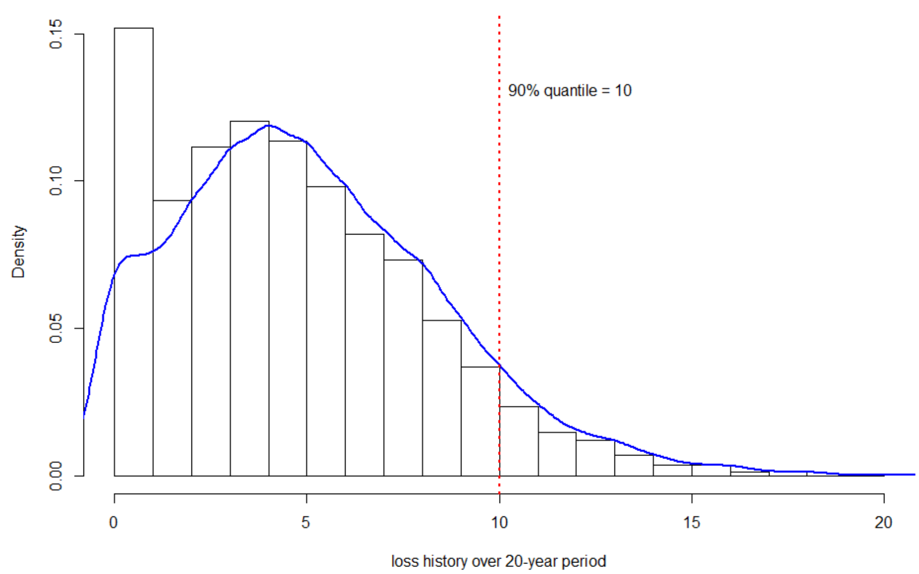


Panel (c) Regression using Truncated Data

Figure 1: An Illustrative Example for the Theoretical Framework



Panel (a) Histogram and Kernel Density Plot for Intensity Criteria



Panel (b) Histogram and Kernel Density Plot for Frequency Criteria

Figure 2: Intensity and Frequency Criteria for Identifying Net Recipients

Table 1. Summary Statistics over Two Groups

	Actuarially-fair		Net recipient		Difference	
	Mean	Stand. dev.	Mean	Stand. dev.	Level	Percentage
Loss ratio (ratio)	0.824	0.345	2.084	0.811	1.260	152.9%
Land value ($/acre)	3212.462	2215.159	3206.125	2497.183	-6.337	-0.2%
Winter temp. (ºC)	4.504	5.277	5.128	5.910	0.625	13.8%
Spring temp. (ºC)	15.527	4.250	15.402	5.340	-0.125	-0.8%
Summer temp. (ºC)	26.993	3.672	26.354	4.755	-0.639	-2.3%
Autumn temp. (ºC)	16.355	3.957	16.291	5.010	-0.064	-0.3%
Winter prec. (mm/day)	2.385	1.268	2.545	1.495	0.160	6.7%
Spring prec. (mm/day)	2.889	0.935	2.874	1.052	-0.014	-0.5%
Summer prec. (mm/day)	2.830	1.021	2.640	1.036	-0.191	-6.7%
Autumn prec. (mm/day)	2.367	0.784	2.476	0.944	0.110	4.6%
Drought prob. (100%)	0.100	0.099	0.097	0.103	-0.004	-3.6%
Wet spell prob. (100%)	0.062	0.068	0.048	0.042	-0.014	-22.9%
Fertilizer expend. ($/acre)	31.804	29.657	12.547	23.700	-19.257	-60.6%
Irrigated ratio (100%)	0.209	0.257	0.166	0.256	-0.043	-20.4%
Num. of counties	2531		282		-	-

Note: All dollar figures is in 2012 constant dollars. This table reports the summary statistics for the variables of interest over the actuarially-fair and net recipient groups. Counties are assigned into these two groups based on 20-year (1993-2012) average loss ratio.

Table 2: The Baseline Regression Table

	Intensity Criteria			Frequency Criteria		
	(1)	(2)	(3)	(4)	(5)	(6)
	climate variable	climate variable × net recipient dummy	(1) + (2)	climate variable	climate variable × net recipient dummy	(4) + (5)
Panel A: Seasonal Average Temperature						
winter	-0.065***	0.123***	0.057	-0.069***	0.111***	0.042
	(0.011)	(0.032)	(0.031)	(0.011)	(0.030)	(0.029)
spring	0.221***	-0.211**	0.009	0.227***	-0.142**	0.085
	(0.029)	(0.096)	(0.097)	(0.033)	(0.072)	(0.071)
summer	-0.346***	0.156***	-0.189***	-0.363***	0.0754	-0.288***
	(0.050)	(0.050)	(0 .062)	(0.049)	(0.049)	(0.065)
autumn	0.008	-0.206	-0.197	0.026	-0.125	-0.099
	(0.046)	(0.129)	(0.128)	(0.050)	(0.136)	(0.133)
Panel B: Seasonal Total Rainfall						
winter	0.034	0.182**	0.216**	0.047	0.004	0.050
	(0.043)	(0.079)	(0.080)	(0.043)	(0.065)	(0.068)
spring	0.424***	-1.175***	-0.750***	0.423***	-0.585***	-0.162
	(0.080)	(0.206)	(0.205)	(0.084)	(0.212)	(0.205)
summer	-0.536***	0.588***	0.051	-0.540***	0.497***	-0.043
	(0.079)	(0.133)	(0.145)	(0.081)	(0.125)	(0.136)
autumn	0.028	0.660***	0.687***	-0.005	0.551***	0.546***
	(0.097)	(0.182)	(0.169)	(0.101)	(0.181)	(0.166)
Panel C: Extreme Weather Events						
drought	-0.231***	0.282	0.050	-0.211**	0.0277	-0.183
	(0.0873)	(0.320)	(0.310)	(0.090)	(0.307)	(0.295)
wet spell	-0.00216	-0.525	-0.527	-0.00170	0.262	0.260
	(0.0865)	(0.557)	(0.548)	(0.089)	(0.469)	(0.461)

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: This table presents the predicted marginal effects of climate variables on farmland value using regression estimates from Equation (9). "Intensity Criteria" means the net-recipient dummy is selected based on long run average loss ratio. "Frequency Criteria" means the net-recipient dummy is selected based on long run loss history. The dependent variable is the log of farmland value per acre. The independent variables of interest are seasonal temperature and precipitation, drought and wet spell probabilities. The squared terms of temperature and precipitation are added to capture nonlinear effect. Share of irrigation, fertilizer expenditure, per capital income, and population density are used as socioeconomic controls. Flood frequency ratio, erosion factor, slope steepness, wetland ratio, electrical conductivity ratio, available water capacity ratio, clay content, sand content, longitude, latitude and elevation are included as soil quality controls. The state, year, state-by-year fixed effects are also included in order to control unobservable factors. The coefficients of these controls are suppressed for the purpose of clarity. The full set of regression results is available upon request. The standard errors are heteroscedasticity and spatial autocorrelation consistent à la Conley (2008).

Table 3: The Marginal Effects of Climate Variables for four Subgroups

	Rainfed Group		Irrigated Group	
	(1)	(2)	(3)	(4)
	Actuarially-fair	Net Recipient	Actuarially-fair	Net Recipient
Panel A: Seasonal Average Temperature				
winter	-0.057***	0.011	-0.107***	0.034
	(0.012)	(0.040)	(0.016)	(0.044)
spring	0.189***	-0.046	0.331***	0.063
	(0.030)	(0.092)	(0.063)	(0.094)
summer	-0.358***	-0.236***	-0.285***	-0.124
	(0.050)	(0.073)	(0.055)	(0.075)
autumn	0.046	0.002	-0.189**	-0.274**
	(0.056)	(0.137)	(0.077)	(0.124)
Panel B: Seasonal Total Rainfall				
winter	0.068*	0.231***	0.032	0.289
	(0.041)	(0.073)	(0.055)	(0.135)
spring	0.804***	0.101	0.099	-1.110***
	(0.082)	(0.252)	(0.123)	(0.301)
summer	-0.381***	-0.020	-0.743***	-0.031
	(0.087)	(0.172)	(0.102)	(0.184)
autumn	-0.104	0.182	0.405***	0.841***
	(0.095)	(0.187)	(0.169)	(0.264)
Panel C: Extreme Weather Events				
drought	-0.239***	-0.431	-0.423**	-0.029
	(0.089)	(0.368)	(0.173)	(0.432)
wet spell	0.004	-0.009	-0.037	-0.644
	(0.093)	(0.457)	(0.160)	(0.749)

Standard errors in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01

Note: This table reports predicted marginal effects of climate variables on farmland value using the regression estimates from Equation (10). Each column represents a subgroup discussed in the Section 4.2. For the detailed information on model specifications, please refer to the text and the note of Table 2.