Crop Insurance, Moral Hazard, and Agricultural Land-Use Adaptation to Pre-Plant Precipitation*

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Abstract. Understanding the impact of climate change on economic outcomes requires knowing how decision-makers might adapt to climate change, and how risk management options might affect their adaptation. Agricultural land allocation among crops (cropping pattern) has long been considered an important adaptation strategy for farmers, yet direct empirical evidence on this is scarce. In this paper, we use high-resolution spatial data on cropland use and weather to study farmers' land-use adaptation to weather risk in Illinois, Iowa, Nebraska, and North Dakota for 2001-2014. By exploiting exogenous variation in pre-plant precipitation, as well as a federal crop insurance policy shock in 2009 from the Supplemental Revenue Assistance Payments (SURE) program and the program's termination in 2012, we identify farmers' cropping pattern adaptation to pre-plant precipitation and how the lower deductibles under the SURE program change this adaptation. Our results show heterogeneous effects on adaptation: absent the program, farmers' land-use decisions on corn (a relatively water-sensitive crop) are quite responsive to pre-plant precipitation in North Dakota and Nebraska, but are not very responsive in Illinois and Iowa. In the former states, farmers substitute other crops for corn when faced with pre-plant precipitation extremes. They do the opposite under the SURE program, substituting corn for other crops. The program thus distorts adaptation and promotes risk taking in response to weather risk. Limited adaptation may imply an increase in economic damages as climate change is projected to increase the frequency of extreme precipitation events in the Midwestern United States.

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1 Introduction

As the climate system continues to warm, episodes of extreme precipitation and drought are more likely to occur in both the short-run and the long-run in North America (IPCC 2013; Christensen et al. 2013; Climate Prospectus 2014). Questions about changes in local temperature and precipitation events have been of practical concern to most of society (Brooks, 2013). Agricultural production is of particular importance due to its direct connection to local weather and its related impacts on economic growth (e.g., Dell et al. 2012; Burke et al. 2015), migration (e.g., Feng et al. 2010; Hornbeck 2012), and human conflict (e.g., Miguel et al. 2004; Hsiang et al. 2013). Understanding the impact of climate change on agriculture requires knowing how farmers might adapt to that change.

In the climate economics literature, studies examining adaptation to climate change in agriculture typically identify the extent to which agricultural profits or crop yields are sensitive either to climate variables (e.g., Mendelsohn et al. 1994; Schlenker et al. 2005; Burke and Emerick 2015) or to weather variables (e.g., Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Fisher et al. 2012; Urban et al. 2015). However, the adaptation mechanisms underlying the agricultural outcomes have not been studied explicitly. For instance, in both Mendelsohn et al.'s (1994) seminal paper and Burke and Emerick's (2015) recent paper, crop switching is only suggested as a possible mechanism to explain the findings of relatively low impacts. Similarly, Urban et al. (2015) describe several physiological and agronomic mechanisms by which extremely wet planting conditions could affect maize and soybean yields. The mechanisms themselves have not been studied, due in part to most mechanisms being unobservable to the analyst.

While the underlying adaptation mechanisms are not well studied, research in development economics has shown that farmers' response to weather risk may help to insure them against climate change (Kala 2014; Miller 2014), even though their responses are not sensitive to climate change per se (Kala 2014). Estimating the link between behavioral adaptation and weather risk is a crucial step for explaining why crop yields may or may not be sensitive to climate change or extreme weather, and for examining how crop choice and supply ultimately may shift in response to climate change.

Understanding farmers' adaptation to weather risk will also be useful for designing government programs to efficiently deal with the risk (Mendelsohn 2000). Existing agricultural programs, such as the disaster payment program and the subsidized crop insurance program, are mainly aimed at moderating the impact of episodes of extreme weather. These programs, historically, have provided generous financial assistance to farmers in the United States and other developed countries (Smith and Goodwin 2010). The importance and cost of these programs might only increase given that episodes of extreme temperature and precipitation are more likely under a changing climate.

These same government programs, ironically, could introduce incentives for moral hazard, thereby distorting farmers' adaptation decisions and perversely making agriculture less responsive to extreme weather. Annan and Schlenker (2015) are the first to address this topic, finding that the federal crop insurance program gives farmers a disincentive to reduce damage to crop yields from extreme heat during the growing season. In fact, in the U.S. Midwest, most adaptation strategies to

possible weather shocks are taken by farmers before the growing season (Haigh et al. 2015). Because these choices typically are unobserved, the mechanisms underlying how government programs affect farmers' adaptation to weather and weather risk remain an open question.

This paper addresses this question by focusing on the crop-choice decision related to land use, hereafter labelled *cropping pattern*, or how many acres of cropland to allocate to various crops. Cropping pattern is a potential adaptation strategy to weather and, in addition, is susceptible to moral hazard from risk-management programs. We examine the effect of pre-plant precipitation on cropping pattern, as well as whether a change in federal crop insurance policy in 2009 distorts these decisions. In addition to deciding on cropping pattern by early spring, farmers in the Midwest make crop insurance decisions by the March 15 deadline for corn and soybeans. Our identification strategy relies on exogenous variation in pre-plant precipitation, with precipitation measured through this same date, March 15. To test whether moral hazard behavior occurs with the policy change in 2009, we interact random variation in pre-plant precipitation with both the policy change in 2009 and the termination of the policy in 2012. By exploiting these quasi-experiments, we can identify cropping pattern adaptation to pre-plant precipitation and any distortion in adaptation due to the policy.

We investigate these topics using data from four large agricultural states in the U.S. Midwest: Illinois, Iowa, Nebraska, and North Dakota. These states all have high-resolution land-use data on crops dating back at least to 2002.[1] Illinois and Iowa are included in their entirety. In North Dakota, we include the region east of the 100th meridian where farming is possible without irrigation. In Nebraska, we include parts of eastern Nebraska without access to irrigation water.[2] The policy change in 2009 comes from the federal Supplemental Revenue Assistance Payments (SURE) program, which supplemented the federal crop insurance and disaster relief programs. The SURE program was adopted in the 2008 Farm Bill and implemented prior to the 2009 growing season. It ran for only three years, ending after the 2011 growing season. The program substantially reduced deductibles on crop insurance (Shields 2010), thereby introducing incentives for moral hazard into farmer decision-making (Smith and Watts 2010). From the vantage point of an insurance agent, a farmer's hidden action was not merely planting a particular crop. Rather, it was planting a particular crop under adverse weather conditions.

In this setting of exogenous variation in weather, unobserved characteristics of farmers and cropland may be correlated with both cropping pattern and pre-plant precipitation. For instance, pre-plant precipitation is more likely to be lower in a semi-arid area where farmers have adapted to the higher probability of low precipitation. We control for this time-invariant unobserved heterogeneity with fixed effects. By using fine-scale spatial data, we pair a panel of crop-specific land uses with pre-plant precipitation for 2001-2014 at a one-square-mile level, containing 640 acres. According to

[1] With Minnesota and South Dakota, the study area would encompass a block of six contiguous states. They are not included, however, because high-resolution cropland data do not begin for them until 2006.
[2] Groundwater from the Ogallala Aquifer is pumped for irrigation in some but not all of eastern Nebraska.

the Public Land Survey System (PLSS), the one-square-mile blocks of farmland, called *sections*, tend to have only one or a few owners within a section.[3] We employ fixed effects at the section level.

In addition to accounting for unobserved heterogeneity at a fine scale, using the section as the unit of analysis takes advantage of high-resolution weather data and thus circumvents the problem of generating precipitation variables with relatively small variation. Small variation in these variables may arise when large-scale weather data and/or location fixed effects are used. While temperature is a large-scale weather event, precipitation tends to be a micro-scale weather event, i.e., precipitation intrinsically varies more spatially than does temperature because local vegetation and geography can affect it. Mearns et al. (2001) and Fezzi and Bateman (2015) show that past climate impact studies that use aggregated precipitation data to analyze a large spatial scale (such as county level or country level) may fail to capture the high variation of precipitation and thus may underestimate its importance. Fisher et al. (2012) also show that spatial fixed effects can absorb a significant amount of weather variation. Here, we use fine-scale precipitation data to avoid this problem, and we follow Fisher et al. (2012) in testing the variation of precipitation under fixed effects. The fine-scale data in weather and cropping pattern also facilitate estimation of a flexible model that can detect nonlinearities and thresholds in the effect of pre-plant precipitation on cropland allocated to four major crops, similar to the methodology used by Schlenker and Roberts (2009) and Burke and Emerick (2015).

In the 2001-2007 period, we allow for heterogeneous adaptation to pre-plant precipitation by state. Illinois and Iowa are dominated by corn and soybean production, whereas several crops are planted in North Dakota and Nebraska, which suggests that farmers in the latter states may have more options for crop substitution.[4] Our results, in fact, show that farmers in North Dakota and Nebraska are much more sensitive to pre-plant precipitation than farmers in Iowa and Illinois. When pre-plant precipitation is too little or too much, they plant fewer acres in corn, which is relatively water-sensitive, and more acres in soybeans, grassland, and/or wheat. Cropping pattern thus is a major adaptation strategy in these two states. In contrast, cropping pattern is not as sensitive to pre-plant precipitation in Illinois and Iowa during this period. In Illinois, these adaptation effects nevertheless are statistically significant for the three major crops (corn, soybean, and grassland). Iowa appears to combine the ideal climatic and soil conditions for growing corn and soybeans such that they are the optimal choices under a wide range of pre-plant precipitation conditions.

During the SURE regime in 2009-2011, farmers in all four states changed cropping pattern in response to the incentives provided by the program's substantially lower deductibles. Farmers in North Dakota and Nebraska planted more acres in corn and fewer acres in wheat, soybeans, and

[3] A section contains four quarter sections of 160 acres apiece. The quarter section is the land unit that was distributed for free under the 1862 Homestead Act to individuals who agreed to settle and farm the land. It is the original foundation of private ownership. We do not use quarter section as the analytical unit because it does not cover all parts of North Dakota and Iowa. Though we cannot observe the actual size and ownership of each farm, use of section-level observations ensures that the section is managed by a small number of owners or operators.
[4] In addition, evidence shows that North Dakota has experienced substantial land conversion from grassland to cropland in recent years (e.g., Mehaffey et al. 2012; Wright and Wimberly 2013), implying that farmers in North Dakota may be more sensitive to weather variation given that the converted grassland tends to be marginal land.

grassland crops when facing extreme pre-plant precipitation. Although less responsive in magnitude, statistically significant effects were also found for corn and soybeans in Illinois and Iowa. Notably, after the program's termination in the 2012-2014 period, farmers largely reversed course, returning cropping patterns close to the original, pre-program patterns. Moral hazard stemming from the small deductibles for crop insurance under the program provides a clear explanation for the risk taking in 2009-2011. Farmers apparently were able to insure against adverse weather that would hurt output. Subsidized crop insurance was substituting for adaptation as a means of risk management.

The paper proceeds as follows. Section 2 describes the background including related literature, agronomic considerations, and the SURE program. Section 3 describes the empirical strategy. The data are discussed in Section 4. Section 5 presents the main results. Section 6 describes robustness checks on the main results. Section 7 offers concluding remarks.

2 Background

2.1 Related literature

This paper relates to a substantial literature that investigates economic responses to weather variables as a basis for understanding adaptation to climate change. This includes the aforementioned studies on agricultural profits and crop yields (Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Fisher et al. 2012; Urban et al. 2015) in addition to studies that examine, for example, energy consumption (e.g., Davis and Gertler 2015; Mansur, Mendelsohn, and Morrison 2008) and human health (e.g., Barreca et al. 2016; Deschênes and Greenstone, 2011). In this literature, researchers typically apply econometric estimates as a basis for forecasting economic outcomes under mid-century or late-century climate projections.

The paper also relates to an immense agronomic and economic literature on crop choice in which climate variables are among the explanatory factors (e.g., Moore, Gollehon, and Carey 1994). In the Midwest in particular, farmers make many weather-sensitive production decisions by the end of the winter (Haigh et al. 2015). In response to pre-plant precipitation, such decisions may include changes in crops (including cover crops), rotation patterns, tillage practices, fertilizer and pesticide applications, and crop insurance (e.g., Haigh et al. 2015; Malcolm et al. 2012). In this paper, we focus on cropping pattern decisions due to the availability of fine-scale land use data and the limited empirical evidence on the effect of pre-plant precipitation on cropping pattern.

Our work examining behavioral adaptation to pre-plant precipitation also relates to the development economics literature mentioned above (e.g., Miller 2014; Kala 2014; Rosenzweig and Udry 2014), which examines farmers' response to expected precipitation during the growing season. Kala (2014) shows that farmers in India use signals related to onset of the monsoon, such as the first date of monsoon plantings in recent years, to decide on optimal planting time, suggesting that past precipitation information can proxy for the expected onset in the current year. Miller (2014) demonstrates that farmers in India adapt to the expected precipitation during the growing season through crop choice, based on information about precipitation in recent years, soil types, and weather forecasts. Our research is most similar to Miller's research, as crop choice is the adaptation strategy

investigated here. Unlike Miller, who explicitly models predicted growing-season precipitation and its effect on crop-choice decisions, our variable of interest is actual pre-plant precipitation. We treat pre-plant precipitation as a random shock that signals both soil moisture at planting time and precipitation during the growing season, and we estimate whether farmers respond to the shock by changing cropping pattern decisions.

In the context of risk management, our study relates to numerous studies examining the effect of crop insurance program on land use and to a few studies examining the effect of agricultural disaster payments (e.g., Goodwin et al. 2004; Langpap and Wu 2014; Schoengold et al. 2014). The effect of these types of programs on farmers' response to weather has not been examined. We study the SURE program due, in part, to the availability of fine-scale land use data before and after the program was enacted. Moreover, Smith and Watts (2010) developed theoretical and simulation models to show that the SURE program introduced incentives for moral hazard into federal agricultural risk-management programs. Additional study of this program, using causal methods, is warranted.

Finally, our work relates to recent studies that conduct randomized controlled trials in India to elicit the effect of a rainfall insurance program on farmers' response to pre-plant weather risk (e.g., Cole et al. 2014; Mobarak and Rosenzweig 2014). We, in contrast, use the SURE program as a quasi-experiment to examine the effect of an agricultural risk management program on farmers' response to pre-plant weather. Our results are consistent with their findings that a risk management program induces farmers to switch to riskier crop production.

2.2 Precipitation and crop growth in the Midwest

Crops need water to grow. The amount of water available for crop growth in rainfed agriculture depends on the interaction between precipitation and soils' water-holding capacity. In the Corn Belt states of the Midwest, the amount of rainfall is usually favorable and the soil is deep with a high water-holding capacity such that cultivated crops can grow without irrigation. Compared to other crops, corn is sensitive to water stress (Steduto et al. 2012). Anderson et al. (2012) compare the sensitivity of crop growth to water inputs and report that corn is more sensitive to drought than other major crops in this region, such as soybeans, wheat, and alfalfa. Hence when farmers expect a water deficit, they may substitute other crops for corn.[5]

Both precipitation prior to the growing season and precipitation during the growing season are important for crop growth, as this total precipitation supplies the water to crops. Relative to precipitation during the growing season, three specific incentives are provided by pre-plant precipitation for farmers' cropping pattern decisions. First, pre-plant precipitation can affect root growth. Precipitation from October through April is important in this region for recharging soil

[5] In Table 2 of Anderson et al. (2012), the index of water-use efficiency (WUE) is compared across major crops in the United States. The WUE index is used to proxy for a crop's average sensitivity to water. The WUE index of corn is set at 1 as a benchmark. Relative to corn, the WUE indices of the major crops in our study region are: 0.65 for soybeans, 0.71 for wheat, 0.43 for alfalfa, 0.85 for barley, and 0.48 for sunflower. That is, in comparison to corn, other major crops have smaller WUE values, indicating those crops are relatively less sensitive to water input.

moisture for root growth (Neild and Newman 1990). Water from precipitation is stored in soils prior to the growing season, thus making it available for root growth during the growing season.

Second, pre-plant precipitation can affect crop growth through indirect mechanisms. Iowa experienced exceptionally warm winters in 2011 and 2012. Research shows that lower pre-plant precipitation affected insect ecology and water quality, which contributed to poor crop production in those years (Al-Kaisi et al. 2013). At the other extreme, excess pre-plant precipitation can increase the risk of seedling diseases. Farmers may extend the planting period in response to pre-plant precipitation, but this increases the risk of foregoing growth and yield in the late summer (Steduto et al. 2012; Urban et al. 2015).

Third, pre-plant precipitation can affect farmers' expectation of total water available for crop growth. Evidence shows that positive (negative) snowfall anomalies in winter are associated with wetter (drier) than normal conditions during the summer in this region (Quiring and Kluver 2009). Our precipitation data also support this relationship. Thus, the realized lower (higher) precipitation prior to the growing season directly signals to farmers that the likelihood is higher of experiencing drier (wetter) conditions for crop growth.

2.3 The Supplemental Revenue Assistance Payments Program

Since the 1980s, the U.S. government has relied on two policy tools, crop insurance and *ad hoc* crop disaster payments, to help farmers recover from financial losses due to natural disasters (Chite 2008). Two advantages of crop insurance, according to policymakers, are its ability to replace costly disaster payments and to provide assistance to more producers. Relative to disaster payments, insurance is also viewed as providing lower incentives for moral hazard and for planting crops on marginal lands (Glauber and Collins 2002). Hence, since the crop insurance program was first instituted in 1938, subsidy provisions were included in major legislative programs in 1980, 1994, and 2000 to make the program more affordable, and thereby to increase participation rates, in expectation of reducing reliance on *ad hoc* disaster payments (Shields and Chite 2010). However, the program failed to replace disaster payments despite substantial growth in the participation rates.[6]

In an effort to rely on crop insurance instead of disaster programs, Congress authorized a new program in the 2008 Farm Bill, the Supplemental Revenue Assistance Payments program (Shields 2010). The SURE program supplemented the crop insurance program by compensating producers for that portion of crop losses that was ineligible for an insurance indemnity payment, i.e., losses that were part of a policy's deductible. In its formula, the SURE payment increased with the amount of the farmer's insured coverage. To be eligible for the SURE payment, a farmer had to purchase crop insurance on all planted crops. Then to qualify for a payment, the relevant farm: (i) had to be located in a county declared as a disaster by the USDA Secretary or a county bordering a disaster county, or (ii) had to experience crop losses that exceeded 50% of expected yield. The SURE program was in place only a short time, 2008 through 2011. The timeline of the program suggests that farmers did

[6] The U.S. Congress continued to establish *ad hoc* disaster assistance primarily through emergency supplemental appropriations for a wide array of USDA programs. Thirty-nine acts established disaster payments to farmers between 1989 and 2007, and such payments were provided every year during this period (Chite 2010).

not make 2008 planting decisions with information about the program. At the same time, farmers later received SURE payments for 2008 crop losses. We chose to exclude 2008 from the analysis because of this ambiguity about program timing relative to farmer decision-making.

Previous research has argued that the SURE program was likely to encourage moral hazard in crop production decisions by both reducing the deductible at which payments began and converting to a whole-farm revenue approach.[7] First, farmers could insure close to 100 percent of their expected yields when they combined SURE payments and the indemnities received from their insurance policies (Smith and Watts 2010). Before 2008, in contrast, farmers typically were not allowed to insure more than 75 percent of their expected crop yields with the federal crop insurance program. This virtual absence of a deductible under SURE created incentives for risk taking in crop choice and production. Empirical evidence by Bekkerman et al. (2012) shows that the SURE program substantially increased crop insurance participation rates, measured by the ratio of net insured acres to total planted acres at the county level. This increase was strongest in counties where, based on the historical record, producers were more likely to receive SURE payments and thus to exploit opportunities for moral hazard.

Second, SURE payments were based on a whole-farm revenue approach whereas, prior to 2008, disaster payments were based on crop-specific losses. As a result, the SURE program was likely to favor farmers with a single crop, which increased the chance that a farm would drop below its guaranteed revenue threshold at which program payments were triggered. In order to take advantage of SURE payments, farmers might eliminate crops from their rotations, thereby reducing the diversity inherent in a portfolio of crops (Shields 2010). Therefore, changes in crop-choice decisions could be evidence of response to the incentives of the SURE program.

Payments under the SURE program were substantial. Bekkerman et al. (2012) report the 2008 SURE payments as $2.107 billion, which is about five times higher than the Congressional Budget Office's original estimated annual payments under the program, $425 million. The authors had difficulty obtaining a clear and full accounting of SURE program payments. One challenge may be due to the difference between: (i) the year of the crop loss, and (ii) the fiscal year of the SURE payments. The U.S. Government Accountability Office lists payments for fiscal years 2008-2012 at $2.52 billion, with $1.20 billion of those in fiscal year 2010 and $0 payments in fiscal years 2008 and 2009 (USGAO 2014). The $0 payments in the first two years is likely explained by the administrative delay in implementing the program. That is, at least some of the payments in fiscal year 2010 almost certainly were made for crop losses in 2008 and/or 2009. In contrast, the Congressional Budget Office lists fiscal year 2010 payments at a higher level than the USGAO, $1.56 billion (CBO 2011). The general point, though, is that farmers received substantial SURE

[7] Deductibles are a common feature of insurance policy design for reducing moral hazard (Varian 1992). Under the standard deductible, insurance payments equal zero until some threshold level of damage is reached, past which payments equal incremental damage (i.e., damage minus deductible). The deductible reduces the perverse incentive for risk-taking behavior in relation to an uncertain outcome.

payments during the program's short lifetime. Many farmers were purchasing crop insurance to meet the eligibility requirements, and sufficient losses in crop yields were occurring to invoke payments.

3 Empirical model

The objectives of this paper are to investigate (i) farmers' cropping pattern adaptation to weather risk and (ii) the role of government risk management programs in changing farmers' cropping pattern adaptation. We accomplish this by exploiting random year-to-year variation in pre-plant precipitation and the exogenous changes caused by the SURE program in 2008 and the program's termination in late 2011. If the program influenced farmer decision-making, this would be new evidence on how government programs can distort adaptation to weather risk and climate change.

3.1 Conceptual motivation

We motivate the empirical model with a simple example that considers farmer decision-making faced with growing-season weather risk. It begins with conditions before 2008, prior to the SURE program, and continues with an extension to the SURE program after 2008. For sake of illustration, we consider a choice to plant wheat or corn on a farm in North Dakota.

Pre-SURE program. March 15 is the deadline for purchasing federally subsidized crop insurance. The farmer will purchase insurance in any case in our example; but because the insurance is crop specific, the insurance decision is, in fact, the decision on which crop to grow, wheat or corn.

The farmer observes pre-plant precipitation on March 15. Pre-plant precipitation is the signal for soil moisture conditions in early May (the window for planting) and for precipitation during the growing season. Here we posit that pre-plant precipitation is relatively low on March 15, and this signal creates conditional probabilities of two precipitation outcomes for the growing season. Only two outcomes are considered for ease of exposition.

State of nature 1: adequate precipitation for growing both wheat and corn (at probability p_1)

State of nature 2: adequate precipitation for growing wheat, but low precipitation for growing corn (at probability (1 - p_1)).

Profit is generated from allocating the farm's cropland either to wheat (W) or corn (C). Expected profit, by crop, encompasses profit (π) under the two states of nature. These are

$$E\pi^W = p_1\pi_1^W + (1 - p_1)\pi_2^W,$$

and

$$E\pi^C = p_1\pi_1^C + (1 - p_1)\pi_2^C.$$

We posit that, given the relatively low pre-plant precipitation, the expected profit from growing wheat exceeds the expected profit from growing corn, or

$$E\pi^W > E\pi^C.$$

The farmer thus allocates cropland to wheat, not corn, given corn yield's sensitivity to water input. In extrapolating to our empirical analysis, we expect wheat acres to increase, and corn acres to decrease, as pre-plant precipitation decreases to a level of water deficit in North Dakota.

SURE program. The SURE program reduces the deductible on crop insurance; farms with yield losses in the 75-90% range of historical yields now qualify for SURE payments. We suppose, on the farm considered here, that corn yield is below 90% of historical yield in state of nature 2. Conventional profit from corn is now augmented with a SURE payment, with the new profit designated as $\pi_2^{C'}$. With $\pi_2^{C'} > \pi_2^{C}$, we posit that corn production now generates higher expected profit than wheat, or

$$E\pi^{C'} = p_1\pi_1^{C} + (1-p_1)\pi_2^{C'} > E\pi^{W}.$$

The farmer changes crops, now allocating cropland to corn, not wheat. This illustrates the moral hazard related to cropland use created by the SURE program. Once again extrapolating to the empirical analysis, we expect the program to increase corn acres and decrease wheat acres – relative to pre-program levels – over the range of relatively low pre-plant precipitation levels. These are the type of treatment effects associated with the SURE program.

3.2 Model

Previous research has demonstrated a strong nonlinearity in the relationship between precipitation during the growing season and crop yield outcomes (e.g., Burke and Emerick 2015). These findings – that both water shortage and water excess affect yield negatively – motivate our approach to investigating whether farmers adjust cropping pattern based on realized pre-plant precipitation, as explained in sections 2.1 and 3.1. Many of the previous studies use higher order terms of precipitation to capture the nonlinear effect. However, using these functional forms in a panel setting means that a unit-specific mean re-enters the estimation, raising omitted variables concerns, as identification in the panel models is no longer limited to location-specific variation over time (McIntosh and Schlenker 2006). We instead use a piecewise linear approach, following Schlenker and Roberts (2009) and Burke and Emerick (2015). This allows us to identify the effects of both a risk of water shortage and a risk of water excess on farmers' cropping pattern response to pre-plant precipitation. Pre-plant precipitation is measured as precipitation from October 1 to March 15, i.e., precipitation from the end of the previous growing season through the deadline for purchasing crop insurance.

We model log planted acres of a crop in section *i* and year *t* (y_{it}) as a simple piecewise linear function of total pre-plant precipitation with a kink at p_0. The effect of the disaster payment policy change in 2008 on cropping pattern adaptation to precipitation risk is identified with the interaction terms between our pre-plant precipitation variables $prec_{it}$ and a policy dummy $d08_{it}$ equal to 1 if the year is after 2008 until 2011. Moreover, the effect of the termination of the SURE program since 2012 on cropping pattern adaptation to precipitation risk is identified with the other set of interaction terms between our pre-plant precipitation variables $prec_{it}$ and a policy dummy $d12_{it}$ equal to 1 if the year is 2012 or later. We estimate the fixed effects model:

$$y_{it} = \alpha_i + \beta_1 prec_{it;p<p_0} + \beta_2 prec_{it;p<p_0} d08_{it} + \beta_3 prec_{it;p<p_0} d12_{it}$$
$$+ \beta_4 prec_{it;p>p_0} + \beta_5 prec_{it;p>p_0} d08_{it} + \beta_6 prec_{it;p>p_0} d12_{it}$$
$$+ \gamma temp_{it} + \delta_t + t^2 + \epsilon_{it} \quad (1)$$

where the variable $prec_{it;p<p_0}$ is the difference between pre-plant precipitation and p_0 interacted with an indicator variable for pre-plant precipitation being below the threshold p_0. $prec_{it;p>p_0}$ is similarly defined for pre-plant precipitation above the threshold. We allow the data to determine p_0 by looping over all possible thresholds and selecting the model with the lowest sum of squared residuals. The variable $temp_{it}$ is the average pre-plant temperature from October 1 to March 15. α_i are section fixed effects that control for unobserved time-invariant characteristics that affect cropland use, such as climate and soil quality. Because the PLSS aligns with patterns of farm ownership and management, the section fixed effects can also control for unobserved farmer characteristics such as management skills and risk perception.[8] Year fixed effects δ_t account for unobserved common year-specific effects across sections, such as crop prices, and statewide and national policies, such as biofuel policy. Similar to Annan and Schlenker (2015), we include a quadratic time trend t^2, which is common to a state, to control for a yield trend that might affect the cropland use decision.

Our parameters of interest are the set of $\boldsymbol{\beta}$. β_1 and β_4 provide estimates of how farmers' crop acreage decisions respond to pre-plant precipitation before 2008 below and above the threshold, respectively. β_2 and β_5 provide estimates of how farmers change their response to pre-plant precipitation under the SURE program relative to before 2008. Hence, $\beta_1 + \beta_2$ and $\beta_4 + \beta_5$ provide estimates of how farmers respond to pre-plant precipitation under the SURE program below and above the threshold, respectively. β_3 and β_6 provide estimates of how farmers change their response after termination of the SURE program relative to under the program. $\beta_1 + \beta_2 + \beta_3$ and $\beta_4 + \beta_5 + \beta_6$ provide estimates of how farmers respond to pre-plant precipitation after 2012 below and above the threshold, respectively.

The identifying assumption of this estimation strategy is that local pre-plant precipitation shocks are exogenous to the policy changes in 2008 and 2012. We find no evidence that our pre-plant precipitation variable and the policy changes are correlated. More generally, it is unlikely that annual pre-plant precipitation caused a national policy change such as the SURE program, or that the SURE program caused a change in pre-plant precipitation.

A concern arises with observations from 2008. The SURE program was an element of a policy enacted on May 22, 2008, so it is unclear whether farmers would have incorporated information about the program into crop planting decisions by March 15 of that year. We exclude 2008 observations from our main analysis due to this ambiguity, and then include these observations as part of the pre-program period in a robustness check.

[8] We follow Holmes and Lee (2012) in defining section as the unit of analysis and then using section fixed effects to take advantage of the unobserved ownership and management features reflected in a PLSS section.

4 Data

This section describes the data on PLSS sections, cropland, weather, and soil. Section 4.5, importantly, explores the extent of variation in the pre-plant precipitation variables in our set of regression models.

4.1 PLSS Sections

The PLSS imposed a grid of squares on the acquired lands of the early United States. The Fifth Principal Meridian was planned in 1815 to govern the grid for Illinois, Iowa, Nebraska, and North Dakota (Committee on Integrated Land Data Mapping 1982). The legal description of land starts with a quarter section (see footnote 1 for additional description), thus the PLSS provides the foundation for land ownership. We use a GIS data layer for the PLSS (ESRI 2015).

We analyze farmers' cropping pattern at the section level, although our data on cropland use, weather, soil, and irrigation have a higher resolution than the section level, and even higher than the quarter section level. The 1-by-1 mile section grid scale facilitates comparison of grids across years when the grid spacing of the cropland data changed from 56m to 30m during the 2001-2014 study period. The grid scale also makes tractable the analysis of local precipitation impacts.

We study cropping pattern in the entire state of Iowa and Illinois and in the areas east of the 100th meridian in North Dakota and Nebraska, including 28 counties and 66 counties, respectively. We exclude the sections that are less than a regular 1-by-1 square mile. Many of the excluded sections are near a county border. Sections in North Dakota and Nebraska that have irrigated land are also excluded.[9] As shown in Table 1, the study area includes 27,151; 50,020; 45,372; and 14,426 sections in North Dakota, Iowa, Illinois, and Nebraska, respectively.

4.2 Cropland use

The cropland use data are from the National Agricultural Statistics Service's Cropland Data Layer (CDL) program, which provides raster-formatted geospatial data on crops planted and other non-agricultural types of land cover for the United States.[10] Each grid corresponds to a specific crop planted or a type of land cover. The CDL's land cover classifications include over 50 crops and come with a spatial resolution of 30 m or 56 m. Our study area covers the four states that have a relatively long panel of annual CDL data in the Midwest. We begin the study in 2001 because a major change in crop insurance policy that increased subsidies for premiums was enacted with the 2000 Agricultural Risk Protection Act.

We intersect CDL data with the PLSS sections using the Python language for ArcGIS, and calculate acres for each crop planted within a section as an aggregation of the CDL grids within the

[9] The sections containing irrigated agriculture are obtained based on the 250-m scale irrigation map in 2007 from the Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US). The fine-scale irrigation data is publicly available. See Brown and Pervez (2014) for documentation.
[10] Donaldson and Storeygard (2016) highlight the CDL as an example of high-resolution satellite data with promising potential for application in economics.

section. For each state, we construct a balanced panel of planted area for the crops chosen within the PLSS sections for 2001-2014 (2002-2014 for Nebraska). Since CDL data before 2006 are less reliable (with the spatial resolution of 56 m), we focus on crops with high classification accuracy, ranging from 85% to 95%, including corn, soybeans, and spring wheat. In addition, since CDL data are less reliable for differentiating among several land cover types – including alfalfa, fallow/idle cropland, unmanaged grassland, pasture, and hay – these land covers are combined into a single *grassland* land cover category. Planting acreage to crops or land uses in the grassland category is an option for replacing more water-sensitive crops.

Table 1 presents summary statistics for mean area by state for corn, soybeans, spring wheat, and grassland, averaged over the sections and sample period. The most common crops in North Dakota are spring wheat and soybeans, which sum to 228 acres per section. Corn is the most common crop in Illinois and Iowa, with soybeans also grown at high levels. Grassland is a major type of land cover in all four states, especially in North Dakota and Nebraska.

Figure 1 presents acreages of major types of cropland use across years. On average, acreages of corn and soybeans in North Dakota are larger after 2012 than from 2009-2011, which are larger than those before 2008. The differences could be driven by factors such as biofuel policy and unobserved management ability, which we control with fixed effects. Acreages of corn and soybeans are relatively stable across the three periods in other states. Grassland acreage decreases after 2008 in all states, especially in North Dakota, where it decreases over time for the entire study period.

4.3 Weather

Our weather data are an updated version of those used in Schlenker and Roberts (2009), which consists of daily precipitation and maximum and minimum temperatures at 4-by-4 kilometer grid cells for the entire United States for 1950-2014. For each cell, we compute pre-plant precipitation by calculating the accumulated precipitation from October 1 in the previous year to March 15 in the current year. We also compute pre-plant temperature by averaging over the same period for each cell. The temperature data begin as the daily-average temperature. These weather data cells are intersected with the PLSS sections using the Python language for ArcGIS. The pre-plant precipitation and temperature at the section level are then computed by averaging over the intersected cells' pre-plant precipitation and temperature, respectively.

Mean pre-plant precipitation in North Dakota and Nebraska is 127.99 mm and 156.29 mm, respectively, which is substantially lower than the 226.37 mm of Iowa and 380.52 mm of Illinois, as shown in Table 1. Illinois also has relatively larger variation in pre-plant precipitation. Using the raw data, Figure 2 presents different forms of the nonlinear relationship between pre-plant precipitation and corn acreages for each state during the three periods: before 2008, 2009-2011, and 2012-2014. For instance, in North Dakota relatively low pre-plant precipitation occurred during 2001-2007 and after 2012, while relatively high pre-plant precipitation occurred during 2009-2011, as can be seen in Panel (A). Moreover, Figure 2 shows that the relationships between pre-plant precipitation and corn acreages across the three periods in Iowa and Illinois are somewhat similar. However, in North Dakota, and Nebraska, while the relationships between pre-plant precipitation and

corn acreages appear similar between the period before 2008 and the period beginning 2012, the relationships during 2009-2011 appear very different to those during the other two periods.

4.4 Soil

We obtain data on soil characteristics from USDA's Soil Survey Geographic (SSURGO) database. This spatially high-resolution database provides 10-by-10 meter grid cells for the entire United States. We extract data on land capability classification and calculate area-weighted average land capability for each section. Land capability classification shows the suitability of soils for most kinds of field crops. The criteria used in grouping the soils involve the landscape location, slope of the field, depth, texture, reactivity of the soil, erosion hazard, wetness, rooting-zone limitations, and climate, which are associated with both soil water-holding capacity and farmers' cropping pattern decisions. Class 1 and Class 2 are defined as *good quality soils* for cropping. Class 3 and Class 4 are *moderate quality soils* that have severe limitations for cropping and/or require careful conservation practices. *Poor quality soils* in Class 6, Class 7, and Class 8 have very severe limitations that make them generally unsuitable for cultivation. The time-invariant soil data set is used in a robustness check to examine farmers' heterogeneous behavioral adaptations by these three categories of soil quality.

As shown in Table 1, both the mean and standard deviation of weighted land capability are smaller in Iowa and Illinois, indicating that land quality in Iowa and Illinois is generally better than that in North Dakota and Nebraska. Land quality in Nebraska is substantially lower than that in North Dakota. Figure 3 presents the distribution of weighted land capability for our sample in the four states. North Dakota and Nebraska do not have any good quality land with weighted land capability less than 2. North Dakota has a large amount of moderate quality land. Nebraska has a substantial amount of poor quality land, while Iowa and Illinois have only a small amount of poor quality land.

4.5 Variation in pre-plant precipitation

Our empirical approach relies on inter-annual variation in pre-plant precipitation after controlling for section and year fixed effects. A concern with this approach is that the section fixed effects can absorb a significant amount of the variation in our precipitation variables. Following Fisher et al. (2012), we explore how much of the variation is absorbed by the fixed effects. Table 2 summarizes regressions of pre-plant precipitation against three sets of fixed effects: an intercept, section fixed effects, and section and year fixed effects. The table reports three items: R^2; the standard deviation of the residual pre-plant precipitation variation not absorbed by the fixed effects in millimeter equivalent; and the fraction of residuals with an absolute value larger than 10 mm.

In North Dakota, the standard deviation of pre-plant precipitation is 47.5 mm without fixed effects. After including section and year fixed effects, the remaining variation of 21.1 mm provides enough residual variation to implement our semi-parametric approach. This conclusion is reinforced by the standard errors on the various estimated coefficients on the pre-plant precipitation variable in

the (subsequent) main regressions. Of note, the same conclusion applies in the other three states, i.e., the variation in the pre-plant precipitation variables remains large after accounting for fixed effects.

5 Results

Results are reported in three subsections. The first provides the main estimation results for a single crop, corn, which we highlight since it is the most water-sensitive major crop in the Midwest. The second provides estimation results for a single state, North Dakota, which we highlight due to its diversity of crops and land allocations. The third briefly discusses the other three crops and states.

Prior to reporting results, we first provide an explanation of why we do not pool the data and estimate a single regression for each crop that encompasses all four states. After all, the section fixed effects account for a host of relevant time-invariant unobservables at the section level, such as soil quality, climate factors, and even the conditional probability of precipitation during the growing season given pre-plant precipitation. But our focus on cropping pattern and the various crop substitutions that result in substantially different acres (by section) across states to a particular crop provides the rationale for the state-level analysis. We can observe this heterogeneity in the average crop-level land allocations in a section and how these allocations vary across states (Figure 1).

A second factor favoring state-level regressions is the heterogeneity across states in pre-plant precipitation thresholds. In the piecewise linear approach, we allow the data for a state to determine the threshold for each crop by looping over all possible thresholds based on equation (1), and then selecting the model with the lowest sum of squared residuals. As shown in Table 3, the thresholds of pre-plant precipitation for corn vary widely across states: 95 mm in North Dakota, 375 mm in Iowa, 320 mm in Illinois, and 110 mm in Nebraska. With different thresholds across states, the piecewise linear functions will vary substantially across states. To illustrate this, Figure 4 graphs these functions using the regression results.

5.1 The effect of pre-plant precipitation on corn acres

We next turn to the main regression results for corn: overall, the corn results show economically and statistically significant responses to pre-plant precipitation in the study states (Table 3). States with relatively poorer natural capital in their climate and soil conditions were more responsive – these are North Dakota and Nebraska. Iowa and Illinois were less responsive to pre-plant precipitation and its interaction with the SURE program.

5.1.1 North Dakota is quite responsive to pre-plant precipitation and its interaction with the SURE program

Table 3 presents our main estimation results for the effects on corn acreage of pre-plant precipitation and the interaction of pre-plant precipitation with the SURE program. Column (1) reports the results for North Dakota. Before the policy change in 2008, a 1 mm decrease in pre-plant precipitation below the threshold decreases corn acreage by 1.1 percent, while a 1 mm increase in pre-plant precipitation above the threshold decreases corn acreage by 0.5 percent. The results imply that farmers adapted to abnormal pre-plant precipitation by planting fewer acres in corn. This adaptation

strategy was adopted even though the federal crop insurance program was in place. The insurance program had created moral hazard problems even before 2008 (Roberts et al. 2011).

Under the SURE policy regime during 2009 to 2011, we do not obtain a statistically significant effect below the threshold as there are only 80 observations in this range in North Dakota in this period. However, above the threshold, we find that a 1 mm increase in pre-plant precipitation actually *increases* corn acreage by 0.4 percent, which is the sum of the coefficients -0.005 and 0.009. The result suggests that farmers chose to grow corn despite the risk of excess precipitation, implying that the program introduced moral hazard into land-use decisions in North Dakota.

Results from after the termination of the SURE program in 2012 only strengthen this perspective. Here, a 1 mm increase in pre-plant precipitation *deceases* corn acreage by 0.4 percent, which is derived as the sum of -0.005, 0.009, and -0.008. Notice that the effect returns to a similar slope as before the SURE program was enacted, i.e., the increase of the corn acreage function due to the new policy in 2008 was virtually offset by the decrease due to termination of the policy in 2012. This lends credibility to the interpretation of the SURE program creating a causal effect.

Figure 4 illustrates the piecewise-linear estimation results for North Dakota in Panel (A). Before 2008, corn acreage increases linearly up to the endogenous threshold of pre-plant precipitation (95 mm) and then decreases linearly above that threshold; the green dashed line depicts this inverted-V-shaped effect. Under the SURE policy, the relationship changes dramatically to a V-shaped effect, as shown by the red dashed line. However, after the program's termination, the relationship returns to virtually the original inverted-V-shaped effect of pre-2008; this is the blue dashed line in the figure.

5.1.2 Nebraska is responsive to pre-plant precipitation

Like North Dakota, Nebraska shows responsiveness in corn acres as a function of pre-plant precipitation, as shown in column (4) of Table 3 and Panel (D) of Figure 4. Before the policy change in 2008, a 1 mm decrease in pre-plant precipitation below the threshold decreases corn acreage by a substantial 2.3 percent. After the policy change in 2008, the estimated coefficient of 0.031 shows a substantial increase in corn acres, such that a 1 mm decrease now increases acreage by 0.8 percent. Farmers thus are willing to risk corn production in the face of a water deficit, apparently due to the risk protection of the SURE program. Following the program's termination, farmers return to fewer corn acres when faced with pre-plant precipitation below the threshold.

Above the threshold in Nebraska, we find a similar pattern to North Dakota's result before 2008 and during the SURE policy. But the estimates are smaller, and we find no evidence about corn acreage change after termination of the SURE program. The results suggest that above the threshold, corn acreage in Nebraska is not as sensitive to the policy changes as in North Dakota.

5.1.3 Iowa and Illinois are generally less responsive to pre-plant precipitation and its interaction with the SURE program

Relative to North Dakota and Nebraska, farmers are less responsive in Iowa and Illinois, where both mean pre-plant precipitation and soil quality are much higher. Table 3 presents the estimation

results and Figure 4 illustrates the piecewise-linear functions for the two states. Before 2008, the estimated coefficients on pre-plant precipitation are not statistically significant in Iowa. Iowa appears to combine the ideal climatic and soil conditions for growing corn such that it is the optimal choice under a range of pre-plant precipitation conditions. In Illinois, the coefficients are statistically significant and indicate a small 0.1 percent decrease in acres given a 1 mm decrease (increase) in pre-plant precipitation below (above) the threshold. Though small, adaptation is occurring in Illinois with farmers planting fewer corn acres as pre-plant precipitation becomes more extreme.

Three of four treatment effects are statistically significant under the SURE program. The effect about the threshold in Iowa is similar in magnitude to that in North Dakota; a 1 mm increase in pre-plant precipitation increases corn acreage by 0.5 percent. After program termination in 2012, the decrease in the corn acreage function literally offsets this effect. Farmers reverse course, once again supporting the idea that the SURE program generates a causal effect.

The pairing of high quality soils and plentiful precipitation for corn growth leads to these generally small responses in Iowa and Illinois. These conditions represent much of the natural capital that underlies the production technology for agriculture in these states. In short, in Illinois and Iowa, corn is not a marginal crop as a function of pre-plant precipitation.[11]

5.2 Cropping pattern in North Dakota

We return to the perspective of cropping pattern in describing results for North Dakota's diverse mix of corn, grassland land cover, soybeans, and spring wheat. Table 4 reports regression results and Figure 5 graphs the results. We learned that North Dakota farmers are responsive in corn acres: in the pre-2008 period, corn acres decrease as pre-plant precipitation decreases (increases) below (above) the threshold. What substitutes for corn during this period? Below the threshold, soybean acres increase substantially as precipitation decreases. Wheat, however, responds like corn, and grassland acres show no effect. Above the threshold, all three crops respond positively to pre-plant precipitation in substituting for corn. In fact, all twelve estimated coefficients above the threshold are statistically significant.

When treated with the SURE program, corn acres shift upward while wheat, soybeans, and grassland acres generally shift downward.

Termination of the SURE program generated statistically significant responses both above and below the precipitation thresholds. Above the thresholds, the acreage relationships for corn, grassland, and wheat returned toward the relationship that held before the program. This also was true for wheat below the threshold. Soybean acres curiously shifted to augment rather than mitigate the effect of the SURE program.

Overall, farmers in North Dakota show adaptation to pre-plant precipitation through cropping

[11] Although corn is not marginal, the corn-soybean rotation over years is a common feature of Iowa and Illinois agriculture (see, e.g., Livingston, Roberts, and Zhang 2015).

pattern followed by moral hazard in cropping pattern under the SURE program.

5.3 Other crops and states

The other main results include grassland land covers and soybeans in states other than North Dakota. In general, grassland acres show statistically significant but small responses to pre-plant precipitation (Table 5). Nebraska and Illinois show similar patterns here. In particular, when the SURE program is interacted with pre-plant precipitation, farmers substitute away from grassland acres both above and below the respective precipitation thresholds. These effects are quite small, with estimated coefficients in the 0.001 to 0.004 range in absolute value. Much of the substitution in these states is toward corn, once again demonstrating SURE's incentive for risk taking in corn production.

Soybean acres similarly show small responses to pre-plant precipitation, and with fewer estimated coefficients showing statistical significance (Table 6). Like corn, soybeans are not a m is not a marginal crop as a function of pre-plant precipitation in Iowa and Illinois. Nevertheless, soybeans are part of the cropping pattern response to the SURE program. Farmers substitute away from soybeans below the thresholds in Iowa and Illinois; and above the threshold in Iowa. Following termination of the SURE program, farmers return to their pre-program response to precipitation above the thresholds in Iowa and Illinois. In Nebraska, there is substitution toward soybean acres, both below and above the threshold, in response to the SURE program.

6 Robustness checks

In this section, we explore the sensitivity of our results to different modeling choices. Overall, our parameter estimates of interest are somewhat sensitive to soil quality categories, but are not sensitive to inclusion of observations from 2008 in the control period 2001-2008, potential endogenous variables, and sections having zero acres of the crop during the entire study period.

6.1 Allowing heterogeneity across soil quality categories

The first check examines whether our results are sensitive to different categories of soil quality, where Figure 3 shows variation in quality by state. We estimate the impact separately with regressions for each of three categories of soil quality based on weighted land capability. Good-quality soil covers the sections with weighted land capability from 1 to 2.99. Moderate-quality soil covers the sections with weighted land capability from 3 to 4.99. Poor-quality soil covers the sections with weighted land capability from 5 to 8. The main regression results capture soil quality in the section fixed effects. Here, in contrast, we examine whether separating the observations by these three categories generates distinct results, in effect demonstrating how the spatial microdata on soil quality can translate into refined results on the effect of pre-plant precipitation on crop acres.[12]

We report results for North Dakota (Table 7), as North Dakota has the largest number of sections across the range of high-, medium-, and low-quality soils.[13] In the main results, we learned that, for

[12] These new regressions still include section fixed effects.
[13] Regression results by category of soil quality are available for the other states upon request to the authors.

the four crops, all twelve estimated coefficients on variables above the respective precipitation thresholds are statistically significant. Do these estimates vary substantially by category of soil quality? Soybeans and grassland acres respond across the range of soil categories in ways that are consistent with the signs and magnitudes of the main results. In contrast, for both corn and wheat, estimated coefficients from regressions on land with high and moderate quality soil are quite similar to the main regressions, but coefficients from regressions on land with low quality soil are marginally significant or insignificant. In this case, farmers are not adjusting corn and wheat acres in response to pre-plant precipitation above the thresholds for these two crops.

Below the precipitation threshold, wheat acres show statistically significant responses across the range of soil qualities. In the main results, the SURE program interacts with pre-plant precipitation to generate a surprisingly large decrease in wheat's acreage function below the threshold (Table 4). This is followed by a large increase following termination of the program. When estimated by soil type, the first effect occurs with the high-quality soil category, and not with the medium- or low-quality soil categories (Table 7). The second effect also occurs with the high-quality soil category; but, worth noting, it is not even estimated for the medium- and low-quality categories due to insufficient observations of pre-plant precipitation below the threshold on sections with these soil types in the period after 2011.

Farmers' decisions on corn and soybeans acres also vary by soil quality when pre-plant precipitation is below the respective thresholds. Adaptation in corn is occurring on land with moderate and low quality soils, but not high quality soils. In contrast, adaptation in soybeans is occurring solely on land with high quality soil.

Overall, farmers in North Dakota are utilizing differences in land quality differently depending on the crop and the regime of pre-plant precipitation (water deficit or water surplus). The regressions by soil quality category generate a certain acuity by revealing that the statistically significant estimates are sometimes concentrated in one or two categories of soil quality instead of occurring across all three categories. When significant, the estimated coefficients from these regressions are very similar in sign and magnitude to the estimated coefficients in the main regression results. In this regard, the main results are reasonably robust to this alternative specification.

6.2 Removing sections that have zero acres of a crop during the study period

The second robustness check examines whether the results would change if we removed the observations from the small number of sections that have zero acres of a crop during the entire study period. As shown in columns with (d) in Table 8, the estimated effects of pre-plant precipitation on corn acreage under the different policy regimes are almost the same as our main results reported in Table 3. This is not surprising because the shares of the sections with zero corn acres during the study period are very small in each of the four states. The same conclusion applies for the other crops in the four states.

6.3 Treating 2008 as a control year

The third robustness check examines whether our results are sensitive to inclusion of observations from 2008 as part of the pre-program period, i.e., expanding the period to 2001-2008 rather than 2001-2007. Here we consider these observations as not subject to the policy change since the SURE program was enacted on May 22, 2008, substantially after farmers had planted that year. Moreover, this program was the most complex program that USDA's Farm Service Agency had undertaken, such that it took some time to educate farmers about the program (Shields 2010). In columns with (e) in Table 8, we observe that the estimated effects of pre-plant precipitation on corn acreage under the different policy regimes are similar to our main results reported in Table 3 or columns with (d) in Table 8. The same conclusion applies for the other crops in the four states.

6.4 Including potential endogenous variables

The fourth robustness check examines potential endogenous variables that may be correlated with both pre-plant precipitation and cropping pattern decisions. These variables include the interaction term between pre-plant precipitation and temperature, aggregated precipitation from March 16 to May 31 (where May 31 is the last planting date in this region as required by the crop insurance policy), average temperature from March 16 to May 31, and total precipitation in the prior growing season from April to September. As reported in columns with (f) in Table 8 for corn, the coefficients of our pre-plant precipitation variables under different policy regimes retain the same sign with similar magnitudes and statistical significance when compared to our main estimation results, as reported in Table 3. The same conclusion applies for the other crops in the four states.

7 Conclusion

This paper analyzes farmers' cropping pattern decisions as a mechanism for adaptation to pre-plant precipitation and as a risk-taking response to the interaction of pre-plant precipitation and federal crop insurance. We apply high-resolution spatial data from four major agricultural states for 2001-2014, and we exploit exogenous variation in pre-plant precipitation that signals weather risk along with exogenous policy changes at the beginning and end of the SURE crop insurance program. Our approach captures the nonlinear relationship between crop acres and pre-plant precipitation and controls for unobserved heterogeneity at the PLSS section level.

Our results demonstrate considerable heterogeneity across crops and states in adaptation and risk taking related to cropping pattern as a function of pre-plant precipitation. Farmers' planting decisions in North Dakota and Nebraska are quite responsive to pre-plant precipitation. When faced with relatively low or relatively high pre-plant precipitation in the pre-program period, farmers in North Dakota and Nebraska typically adapted by substituting away from corn and toward soybeans, spring wheat, and grass-like crops. With the lower deductibles under the SURE program beginning in 2009, these cropping-pattern adjustments were largely reversed, with corn acres increasing at the expense of the other crops. Following the program's termination, farmers largely reverted to the pre-program cropping pattern, lending credibility to a causal interpretation of the program's impact. The SURE program thus promoted risk taking in corn production in the face of extreme pre-plant

precipitation. While previous research raised concern about moral hazard with the SURE program (e.g., Bekkerman et al. 2012; Smith and Watts 2010), it had not been demonstrated empirically.

We find that farmers' cropping pattern decisions in Illinois and Iowa are generally less responsive to pre-plant precipitation and its interaction with the SURE program. The results show, in effect, that corn and soybeans are not marginal crops relative to the existing range of pre-plant precipitation in those states. The corn-soybean rotation over years is a staple of agriculture in Illinois and Iowa and, in fact, is optimal under a wide variety of conditions (Livingston et al. 2015). At the same time, when pre-plant precipitation is interacted with the SURE program, farmers do exhibit risk taking, tending to plant more acres in corn and fewer acres in soybeans.

Two extensions of the existing analysis are currently underway. One is to study the productivity impacts of pre-plant precipitation. Similar to Annan and Schlenker (2015), the idea is to assess whether the SURE program, interacted with pre-plant precipitation, resulted in lower yields of corn due to the risk taking already discovered in the cropping pattern results. The second extension applies the notion of *selection on moral hazard* (Einav et al. 2013), namely that farmers' selection of crop insurance coverage could be affected by their anticipated cropping pattern response to the coverage. We are preparing measures of insurance demand and will be investigating whether crop-specific insurance demand, like crop acreage, follows a piecewise linear response to pre-plant precipitation. Both extensions will rely on county-level data from USDA agencies rather than fine spatial data.

Direct evidence about farmers' adaptation to weather and weather risk is crucial for understanding the impact of climate change and for designing efficient adaptation policy – after all, climate change is a change in weather risk. Looking to the future, the major climate vulnerability for the agricultural sector in the Midwest is risk of excess precipitation (Andresen et al., 2012). Widespread flooding events, given persistent patterns of heavy rainfall, already occur over much of the region, and excessive rainfall events occur over localized areas during the summer. Existing climate trends exacerbate these anomalies, trends such as increased precipitation and increased extreme precipitation (Andresen et al., 2012). Future climate projections at the end of the century for the Midwest come with substantial uncertainty, yet the projections include increased precipitation, increased extreme precipitation, and little change or even a small decrease in summer precipitation (Winkler et al., 2012). Following the methodology developed in Dell, Jones, and Olken (2014), additional research is needed to investigate the effect of existing climate change on land-use change in the nationally important Midwest agricultural sector.

A challenge for public policymakers and private risk managers is to design efficient risk-management policies in an environment of climate change. Policies need to encourage efficient adaptation and, thus, must account for perverse incentives for risk taking provided by federal insurance programs. Our analysis showed clearly that lower deductibles for crop insurance promoted risk taking by farmers facing extreme pre-plant precipitation. Future research along these same lines is needed across a range of sectors and activities to understand the interrelationship among private decision-making under risk, public policy related to private insurance, and climate change.

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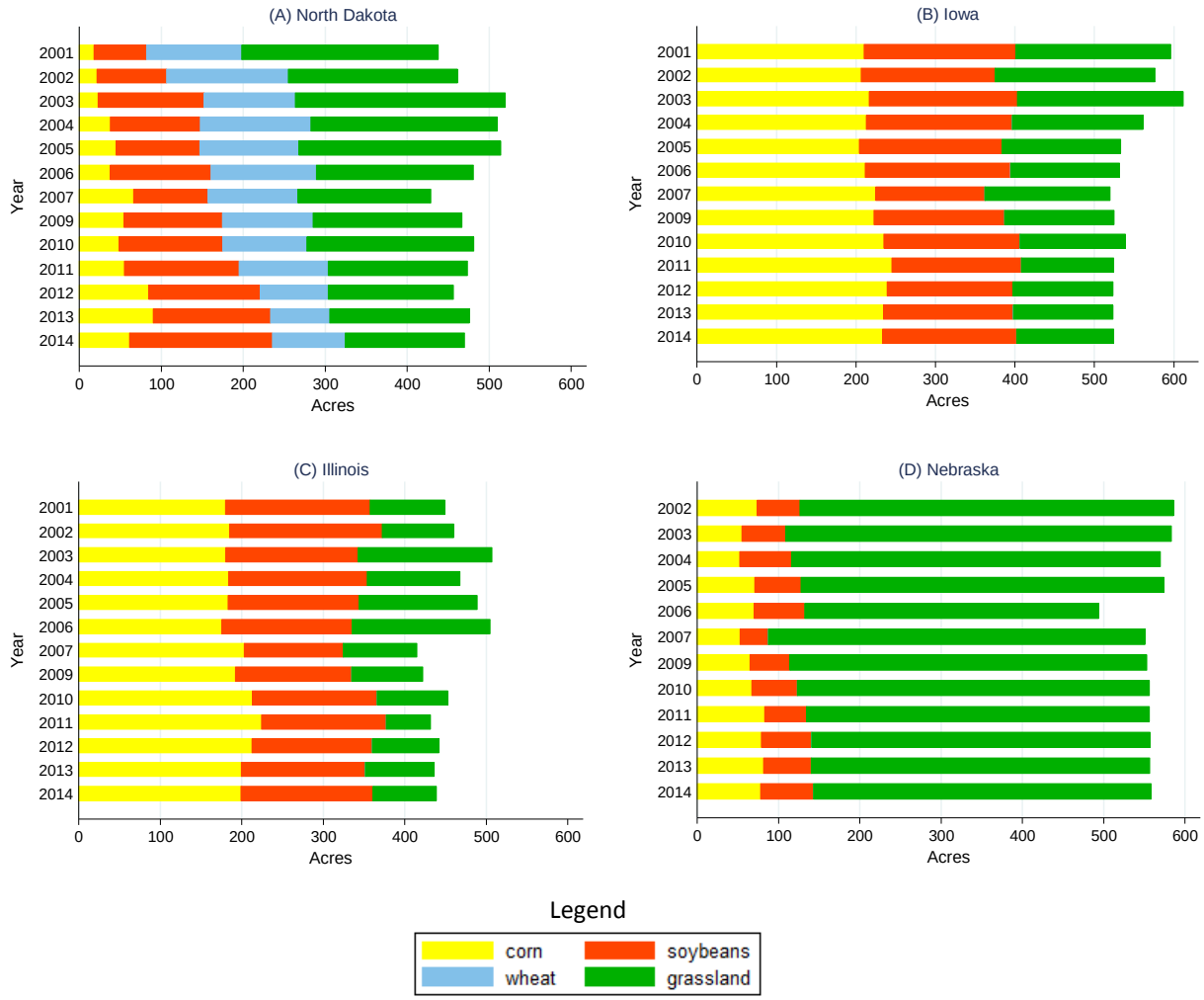
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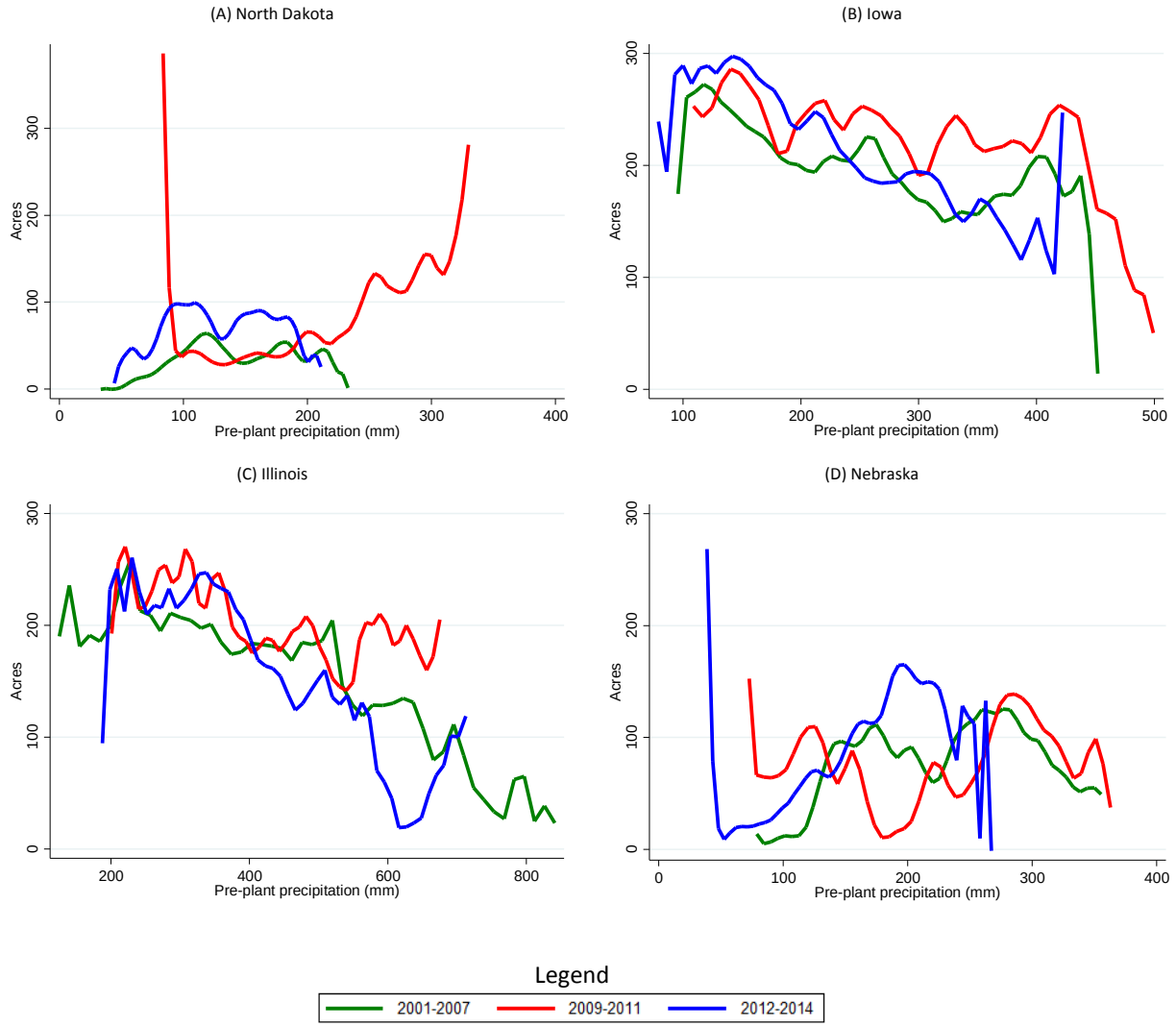
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Figure 1: Average Cropland and Grassland Acres at the Section Level



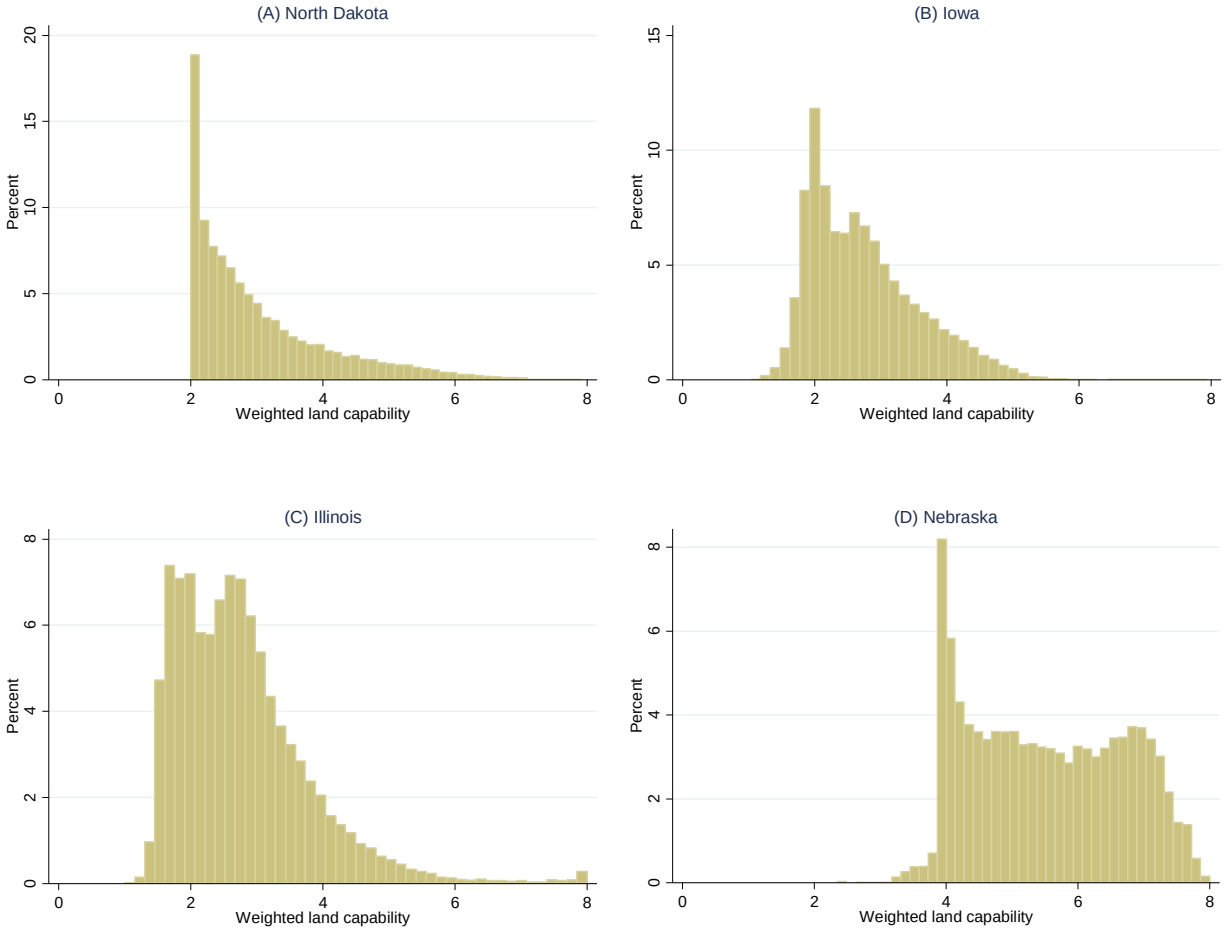
Notes: The graphs display acreages of major types of cropland use across years. Data at the section level are extracted from the Cropland Data Layer. Panels (A)-(D) use non-irrigated PLSS sections.

Figure 2: Relationship between Corn Acres and Pre-Plant Precipitation



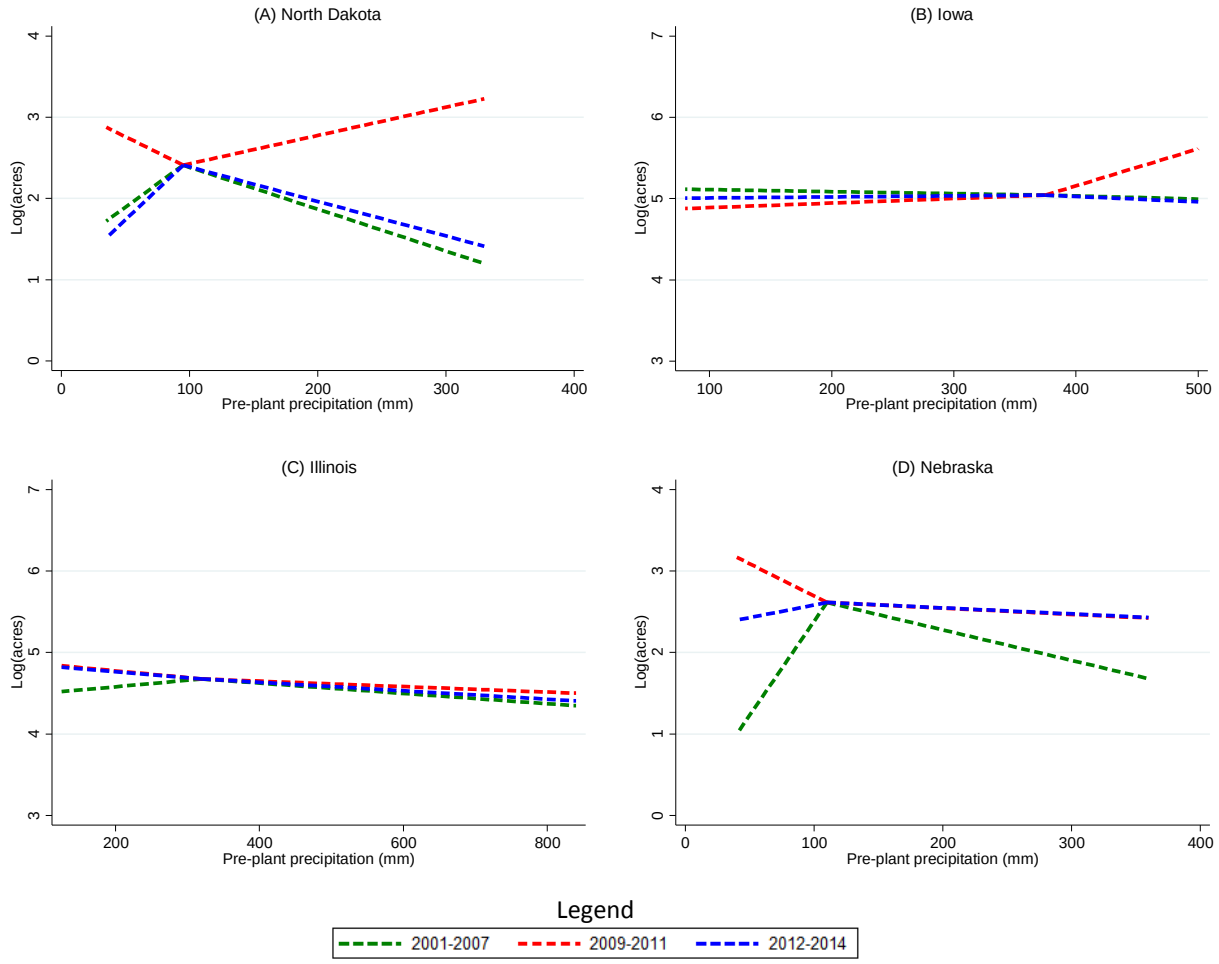
Notes: These plots are generated by Kernel-weighted local polynomial smoothing with the settings: kernel = epan2, degree = 3, and bandwidth = 20. Data at the section level are extracted from the Cropland Data Layer and Schlenker and Roberts (2009) weather data. Panels (A)-(D) use non-irrigated PLSS sections. Pre-plant precipitation is in millimeters.

Figure 3: Land Capability Class



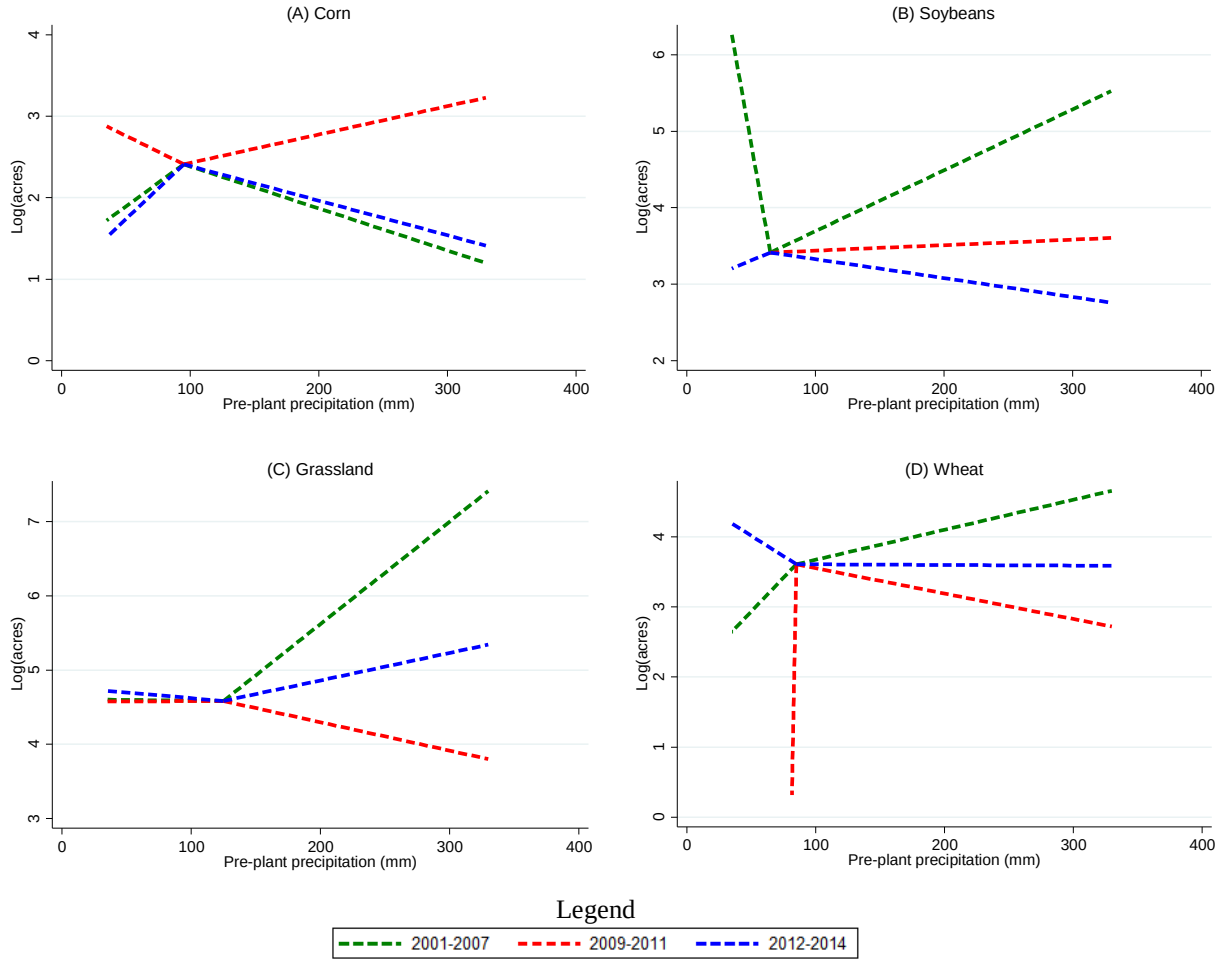
Notes: The histograms display the percentage of sections belonging to a class of weighted land capability. Weighted land capability is calculated by the authors with the Soil Survey Geographic (SSURGO) database. Larger values indicate poorer soil quality. Panels (A)-(D) use non-irrigated PLSS sections. See Section 4.4 for our calculation of weighted land capability at the section level.

Figure 4: Predicted Effects of Pre-plant Precipitation on Corn Acres; by Policy Regime



Notes: The graphs display the predicted means of log(corn acres) in the sections as a function of pre-plant precipitation. Panels (A)-(D) use non-irrigated PLSS sections. Pre-plant precipitation is in millimeters.

Figure 5: Predicted Effects of Pre-plant Precipitation on Cropland Acres in North Dakota; by Policy Regime



Notes: The graphs display the predicted means of log(crop acres) in the sections as a function of pre-plant precipitation. Pre-plant precipitation is in millimeters.

Table 1: Summary Statistics of Crop Planting Area at the Section Level

		North Dakota			Iowa		
	Unit	Mean	Median	S.D.	Mean	Median	S.D.
Corn[a]	acre	49.51	6.75	88.29	222.85	222.30	134.61
Soybeans[a]	acre	118.74	71.10	132.80	170.63	162.23	116.05
Spring wheat[a]	acre	110.49	72.13	120.68	0.10	0	1.79
Grassland[a]	acre	196.52	149.85	172.58	151.82	111.83	131.21
Pre-plant precipitation[b]	mm	127.99	122.04	47.49	226.37	218.53	67.36
Pre-plant temperature[b]	Celsius	-6.19	-6.55	2.24	-0.65	-0.68	2.13
Weighted land capability[c]	index	3.03	2.68	1.05	2.74	2.59	0.83
Sections			27,151			50,020	
Observations			352,963			650,260	
		Illinois			Nebraska		
		Mean	Median	S.D.	Mean	Median	S.D.
Corn[a]	acre	194.71	181.10	146.88	68.95	9.68	99.23
Soybeans[a]	acre	157.77	145.13	119.55	55.51	1.35	90.68
Spring wheat[a]	acre	0.00	0	0.30	0.01	0	0.51
Grassland[a]	acre	102.67	74.70	97.40	433.52	501.76	199.43
Pre-plant precipitation[b]	mm	380.52	360.06	108.55	156.29	145.84	52.11
Pre-plant temperature[b]	Celsius	2.74	2.77	2.28	0.70	0.77	1.68
Weighted land capability[c]	index	2.77	2.61	1.01	5.52	5.45	1.15
Sections			45,372			14,426	
Observations			589,836			173,112	

Notes: [a]Authors' calculations with the Cropland Data Layer, 2001-2014.

[b]Authors' calculations with Schlenker and Roberts (2009) weather data, 2001-2014.

[c]Authors' calculations with the Soil Survey Geographic (SSURGO) database. Larger values indicate poorer soil quality. See Section 4.4 for our calculation of weighted land capability at the section level.

Table 2: Variation of Pre-Plant Precipitation under Various Sets of Fixed Effects

		(1)	(2)	(3)
		R^2	σ_e	|e| > 10mm
North Dakota	No FE	-	47.5 mm	83.8%
	Section FE	0.116	44.7 mm	86.4%
	Section FE + year FE	0.802	21.1 mm	57.8%
Iowa	No FE		67.4 mm	91.7 %
	Section FE	0.270	57.5 mm	87.0 %
	Section FE + year FE	0.832	27.6 mm	73.4 %
Illinois	No FE		108.6 mm	93.2 %
	Section FE	0.419	82.8 mm	89.7 %
	Section FE + year FE	0.784	50.4 mm	83.6 %
Nebraska	No FE		52.1 mm	85.9 %
	Section FE	0.177	47.3 mm	83.1 %
	Section FE + year FE	0.779	24.5 mm	67.2 %

Notes: This table summarizes regressions of pre-plant precipitation on various sets of fixed effects to assess how much variation is absorbed by the fixed effects (FE). Column (1) reports the R^2 of the regressions. Column (2) reports the standard deviation of the residuals (remaining pre-plant precipitation variation) in millimeters. Column (3) reports the fraction of the observations having a residual larger than 10 mm.

Table 3: Estimation Results for Corn

	(1)	(2)	(3)	(4)
	North Dakota	Iowa	Illinois	Nebraska
Pre-plant precipitation below threshold	-0.011*	0.000	-0.001**	-0.023***
	(0.006)	(0.000)	(0.000)	(0.007)
Pre-plant precipitation below threshold	0.019	-0.001***	0.002***	0.031***
× after 2008	(0.052)	(0.000)	(0.000)	(0.007)
Pre-plant precipitation below threshold	-0.023	0.000*	-0.000	-0.011***
× after 2012	(0.052)	(0.000)	(0.001)	(0.003)
Pre-plant precipitation above threshold	-0.005***	-0.000	-0.001***	-0.004***
	(0.002)	(0.003)	(0.000)	(0.001)
Pre-plant precipitation above threshold	0.009***	0.005*	0.000	0.003***
× after 2008	(0.002)	(0.003)	(0.000)	(0.001)
Pre-plant precipitation above threshold	-0.008***	-0.005**	-0.000	0.000
× after 2012	(0.003)	(0.002)	(0.000)	(0.001)
Pre-plant temperature	-0.124	-0.014	0.025	-0.109**
	(0.075)	(0.017)	(0.045)	(0.052)
Observations	352,963	650,260	589,836	173,112
R-squared	0.155	0.024	0.024	0.086
Number of PLSS sections	27,151	50,020	45,372	14,426
Threshold of pre-plant precipitation	95	375	320	110

Notes: Dependent variable in all regressions is the log of corn acres. All regressions include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regressions (1)-(4) use non-irrigated PLSS sections. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 4: Estimation Results for North Dakota

	(1)	(2)	(3)	(4)
	Corn	Soybeans	Grassland	Wheat
Pre-plant precipitation below threshold	-0.011*	0.095***	0.000	-0.019***
	(0.006)	(0.030)	(0.003)	(0.005)
Pre-plant precipitation below threshold	0.019	-	-0.000	-0.921***
× after 2008	(0.052)	-	(0.005)	(0.057)
Pre-plant precipitation below threshold	-0.023	-0.102**	0.002	0.952***
× after 2012	(0.052)	(0.038)	(0.004)	(0.059)
Pre-plant precipitation above threshold	-0.005***	0.008***	0.014***	0.004**
	(0.002)	(0.001)	(0.002)	(0.002)
Pre-plant precipitation above threshold	0.009***	-0.007***	-0.018***	-0.008***
× after 2008	(0.002)	(0.002)	(0.003)	(0.002)
Pre-plant precipitation above threshold	-0.008***	-0.003**	0.008**	0.004*
× after 2012	(0.003)	(0.001)	(0.003)	(0.002)
Pre-plant temperature	-0.124	0.076	-0.384***	0.280***
	(0.075)	(0.109)	(0.095)	(0.045)
Observations	352,963	352,963	352,963	352,963
R-squared	0.155	0.159	0.351	0.159
Number of PLSS sections	27,151	27,151	27,151	27,151
Threshold of pre-plant precipitation	95	65	125	85

Notes: Dependent variable in all regressions is the log of acres. All regressions include section fixed effects, year fixed effects, and a quadratic time trend. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 5: Estimation Results for Grassland

	(1)	(2)	(3)	(4)
	North Dakota	Iowa	Illinois	Nebraska
Pre-plant precipitation below threshold	0.000	-0.002	0.002***	0.004**
	(0.003)	(0.001)	(0.000)	(0.002)
Pre-plant precipitation below threshold	-0.000	0.006***	-0.001**	-0.004*
× after 2008	(0.005)	(0.001)	(0.000)	(0.002)
Pre-plant precipitation below threshold	0.002	-0.002*	-0.001	0.002**
× after 2012	(0.004)	(0.001)	(0.001)	(0.001)
Pre-plant precipitation above threshold	0.014***	-0.002***	0.001**	0.003***
	(0.002)	(0.000)	(0.000)	(0.000)
Pre-plant precipitation above threshold	-0.018***	0.001***	-0.000	-0.002***
× after 2008	(0.003)	(0.000)	(0.000)	(0.000)
Pre-plant precipitation above threshold	0.008**	-0.001*	-0.000	-0.002***
× after 2012	(0.003)	(0.000)	(0.001)	(0.001)
Pre-plant temperature	-0.384***	0.031	-0.064	-0.011
	(0.095)	(0.020)	(0.068)	(0.026)
Observations	352,963	650,260	589,836	173,112
R-squared	0.351	0.280	0.337	0.169
Number of PLSS sections	27,151	50,020	45,372	14,426
Threshold of pre-plant precipitation	125	170	430	130

Notes: Dependent variable in all regressions is the log of grassland acres. All regressions include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regressions (1)-(4) use non-irrigated PLSS sections. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 6: Estimation Results for Soybeans

	(1)	(2)	(3)	(4)
	North Dakota	Iowa	Illinois	Nebraska
Pre-plant precipitation below threshold	0.095***	0.001	0.000	-0.002*
	(0.030)	(0.001)	(0.000)	(0.001)
Pre-plant precipitation below threshold	-	-0.004***	-0.002***	0.003*
× after 2008	-	(0.001)	(0.000)	(0.001)
Pre-plant precipitation below threshold	-0.102**	0.001	-0.000	-0.001
× after 2012	(0.038)	(0.001)	(0.000)	(0.001)
Pre-plant precipitation above threshold	0.008***	0.000	-0.001***	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)
Pre-plant precipitation above threshold	-0.007***	-0.001***	0.001***	0.002*
× after 2008	(0.002)	(0.000)	(0.000)	(0.001)
Pre-plant precipitation above threshold	-0.003**	0.002***	-0.002***	0.005**
× after 2012	(0.001)	(0.000)	(0.000)	(0.002)
Pre-plant temperature	0.076	0.093***	-0.055**	-0.146***
	(0.109)	(0.015)	(0.027)	(0.030)
Observations	352,963	650,260	589,836	173,112
R-squared	0.159	0.070	0.080	0.071
Number of PLSS sections	27,151	50,020	45,372	14,426
Threshold of pre-plant precipitation	65	185	385	180

Notes: Dependent variable in all regressions is the log of soybeans acres. All regressions include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Regressions (1)-(4) use non-irrigated PLSS sections. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 7: Estimation Results for North Dakota by Soil Quality Category

	Corn			Soybeans			Grassland			Wheat		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
Pre-plant precipitation below threshold	-0.006	-0.016***	-0.015***	0.104***	0.051	-0.008	-0.002	0.002	0.001**	-0.023***	-0.018***	-0.014**
	(0.008)	(0.003)	(0.002)	(0.028)	(0.040)	(0.033)	(0.004)	(0.001)	(0.001)	(0.006)	(0.005)	(0.006)
Pre-plant precipitation below threshold	0.022	-0.067	-	-	-	-	-0.001	0.002	-0.000	-0.979***	-	-
× after 2008	(0.054)	(0.066)	-	-	-	-	(0.006)	(0.002)	(0.002)	(0.075)	-	-
Pre-plant precipitation below threshold	-0.035	0.076	0.006	-0.115***	-0.045	0.059	0.001	-0.002	-0.000	1.015***	0.026***	0.023**
× after 2012	(0.054)	(0.066)	(0.004)	(0.035)	(0.045)	(0.100)	(0.005)	(0.002)	(0.002)	(0.075)	(0.006)	(0.008)
Pre-plant precipitation above threshold	-0.005**	-0.004**	-0.003	0.008***	0.008***	0.012***	0.013***	0.008***	0.004**	0.005**	0.002	-0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Pre-plant precipitation above threshold	0.008***	0.006***	0.005*	-0.007***	-0.009***	-0.013***	-0.017***	-0.008***	-0.005*	-0.010***	-0.004**	-0.001
× after 2008	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Pre-plant precipitation above threshold	-0.010***	-0.006***	-0.003*	-0.004**	-0.002	-0.002	0.008**	0.001	0.000	0.004	0.004**	0.002
× after 2012	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Pre-plant temperature	-0.137*	-0.091	-0.140	0.072	-0.004	-0.017	-0.498***	-0.130**	-0.070	0.286***	0.218***	0.101
	(0.080)	(0.065)	(0.100)	(0.106)	(0.126)	(0.166)	(0.099)	(0.050)	(0.041)	(0.067)	(0.047)	(0.061)
Observations	219,518	109,109	24,336	219,518	109,109	24,336	219,518	109,109	24,336	219,518	109,109	24,336
R-squared	0.186	0.126	0.072	0.164	0.171	0.138	0.456	0.201	0.063	0.164	0.158	0.228
Number of PLSS sections	16,886	8,393	1,872	16,886	8,393	1,872	16,886	8,393	1,872	16,886	8,393	1,872
Threshold of pre-plant precipitation	95	95	95	65	65	65	125	125	125	85	85	85

Notes: Dependent variable in all regressions is the log of acres. All regressions include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Columns (a), (b), and (c) are separate regressions for high, moderate, and poor soil quality, respectively. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.

Table 8: Robustness Checks for Corn across States

	North Dakota			Iowa			Illinois			Nebraska		
	(1d)	(1e)	(1f)	(2d)	(2e)	(2f)	(3d)	(3e)	(3f)	(4d)	(4e)	(4f)
Pre-plant precipitation below threshold	-0.011*	-0.011**	-0.014**	0.000	0.001**	0.000	-0.001**	-0.001**	-0.001*	-0.023***	-0.019***	-0.023***
	(0.006)	(0.004)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.006)	(0.006)
Pre-plant precipitation below threshold	0.019	0.016	0.024	-0.001***	-0.001***	-0.001***	0.002***	0.002***	0.001	0.031***	0.026***	0.031***
× after 2008	(0.052)	(0.052)	(0.052)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.007)	(0.006)	(0.006)
Pre-plant precipitation below threshold	-0.023	-0.019	-0.028	0.000*	0.000	0.001**	-0.000	-0.000	0.001	-0.011***	-0.011***	-0.012***
× after 2012	(0.052)	(0.051)	(0.052)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.003)	(0.003)	(0.003)
Pre-plant precipitation above threshold	-0.005***	-0.005***	-0.003	-0.000	0.000	0.000	-0.001***	-0.001***	-0.000	-0.004***	-0.003***	-0.004***
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Pre-plant precipitation above threshold	0.009***	0.008***	0.009***	0.005*	0.004***	0.005	0.000	0.000*	0.000	0.003***	0.002***	0.002***
× after 2008	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Pre-plant precipitation above threshold	-0.008***	-0.007**	-0.007**	-0.005**	-0.006**	-0.007**	-0.000	-0.000	-0.001**	0.000	0.000	0.000
× after 2012	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Pre-plant temperature	-0.124	-0.131*	-0.156	-0.014	-0.014	-0.060**	0.026	0.013	0.029	-0.110**	-0.113**	-0.053
	(0.075)	(0.066)	(0.108)	(0.017)	(0.017)	(0.025)	(0.045)	(0.046)	(0.037)	(0.052)	(0.049)	(0.082)
Observations	352,235	380,114	352,963	650,104	700,280	650,260	588,068	635,208	589,836	172,056	187,538	173,112
R-squared	0.155	0.144	0.155	0.024	0.026	0.025	0.024	0.029	0.029	0.087	0.083	0.091
Number of PLSS sections	27,095	27,151	27,151	50,008	50,020	50,020	45,236	45,372	45,372	14,338	14,426	14,426
Threshold of pre-plant precipitation	95	95	95	375	375	375	320	320	320	110	110	110

Notes: Dependent variable in all regressions is the log of acres. All regressions include section fixed effects, year fixed effects, and a quadratic time trend that is common to the state. Columns with (d) drop the sections having zero acres of the crop planted over our sample period. Columns with (e) include observations in 2008 as a control year. Columns with (f) include potential endogenous variables, including aggregated precipitation from March 16 to May 31, average temperature from March 16 to May 31, total precipitation in the prior growing season from April to September, and the interaction term between pre-plant precipitation and temperature. Standard errors are clustered at the county level and shown in parentheses. Significance levels are indicated by *** 1%, ** 5%, * 10%.