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Farming under Weather Risk
Adaptation, Moral Hazard, and Selection on Moral Hazard

Hsing-Hsiang Huang and Michael R. Moore

3.1 Introduction

As the climate system continues to warm, episodes of drought and extreme precipitation are more likely to occur in North America (Christensen et al. 2013). Questions about changes in local temperature and precipitation events have been a practical concern to most of society (Brooks 2013). Agricultural productivity and profitability are of particular importance due to their direct connection to weather (e.g., Deschênes and Greenstone 2007; Fisher et al. 2012; Moore and Lobell 2014). Extreme weather events—including excessive heat, drought, and precipitation—are known to cause harmful impacts on crop yields (Schlenker and Roberts 2009; Lobell et al. 2014; Urban et al. 2015). According to the "smart farmer" hypothesis (Mendelsohn, Nordhaus, and Shaw 1994), however, farmers adapt to weather variation and can adapt to climate change to mitigate these impacts. Yet we know little about the mechanism(s) of adaptation: Is it through crop choice, deployment of farm labor, or timing of production activities? Another possibility is that farmers manage weather risk through crop insurance. As with all insurance markets, crop insurance raises the prospect of market failure through

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adverse selection and moral hazard. The limited evidence on crop insurance suggests that, when treated with extreme heat, production areas with higher levels of insurance generate lower crop yields—that is, insurance may create a moral-hazard incentive for less adaptation (Annan and Schlenker 2015). Once again, the mechanisms underlying this outcome remain unstudied.

In this chapter, we study farmers' crop choice and crop insurance take-up in response to preplant precipitation from the perspectives of adaptation, moral hazard, and selection on moral hazard. Crop choices are analyzed as land use—hereafter labeled "cropping pattern," or how many acres of cropland are allocated to various crops. Cropping pattern is a possible adaptive strategy to preplant precipitation, as crops vary in their physiological requirements for water (Anderson, Wang, and Zhao 2012). At the same time, cropping pattern is potentially susceptible to the moral-hazard incentive of insurance. In addition to deciding on cropping pattern in early spring (Haigh et al. 2015), farmers in the US Midwest make crop insurance decisions by a March 15 deadline for corn and soybeans. Insurance is purchased by crop-specific acreage, and farmers decide on what percentage of yield to insure up to a maximum of 85 percent of the crop's historical average yield (where 85 percent coverage translates into a 15 percent deductible). Our variable for preplant precipitation includes precipitation from October 1 of the previous year through the March 15 insurance deadline. Our identification strategy relies on exogenous variation in this variable—that is, interannual variation in preplant precipitation is plausibly random within a given spatial unit, as with other weather variables (Dell et al. 2014).

In tandem with the weather experiment, we exploit a quasi experiment created by a federal agricultural policy from 2009 to 2011—the Supplemental Revenue Assistance Payments (SURE) program—to examine moral hazard in cropping pattern and selection on moral hazard in insurance take-up. The SURE program augmented private crop insurance (at no charge to the farmer) with what was termed a "shallow loss" provision (Glauber 2013)—that is, a provision to insure against relatively small reductions in crop yields that normally are part of the deductible. The provision substantially reduced deductibles on crop insurance, to 10 percent (Shields 2010; USDA-FSA 2009), thereby increasing the incentive for moral hazard in farmer decision-making (Smith and Watts 2010).[1] 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 conditions of extreme preplant precipitation. By interacting the SURE program and preplant precipitation, we estimate the treatment effect of SURE's reduced deductibles on cropping pattern to generate evidence on moral hazard.

Selection on moral hazard is the idea that an individual's selection of

1. Deductibles are a well-known feature of insurance policy design for reducing moral hazard—that is, reducing the incentive provided by insurance for risk-taking in relation to an uncertain outcome (Varian 1992).

insurance coverage is affected by the expected behavioral response to the coverage (Einav et al. 2013). Einav et al. show, for example, that individuals with a greater behavioral response to a health insurance contract purchase greater coverage. The issue in our study is whether farmers who increase (decrease) a crop's acreage under the SURE program purchase higher (lower) insurance coverage on the crop; this is moral hazard followed by selection on moral hazard. Higher coverage, notably, will generate a larger payout for a given crop yield. We investigate insurance take-up in a similar way to cropping pattern. By interacting the program and preplant precipitation, we estimate the treatment effect of SURE's reduced deductibles on insurance take-up to generate evidence on selection on moral hazard.

We investigate these topics using data from four large agricultural states in the US Midwest: Illinois, Iowa, Nebraska, and North Dakota. Illinois and Iowa are included in their entirety, while only the rain-fed, agricultural regions of North Dakota and Nebraska are included (i.e., irrigated agriculture is excluded as in Schlenker et al. 2005). We apply high-resolution spatial data on land use (crops) and weather.[2] We apply county-level data on insurance take-up and prepare county-level weather data to match the insurance data. Insurance take-up is measured using farmers' expenditures on insurance premiums, as in Deryugina and Kirwan (2018). The study spans 2001 to 2014. With SURE being a short-lived program (2009 to 2011), both the beginning and end of the program are subject to analysis. A key question is, After program termination, does cropping-pattern adaptation to preplant precipitation return to its preprogram status? To implement this, we interact preplant precipitation with both the policy change in 2009 and its termination after 2011.

We estimate piecewise linear regressions, by state and crop, to allow for heterogeneous effects of preplant precipitation across states. 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. Previous research has found a strong nonlinearity in the relationship between precipitation during the growing season and crop yields (Schlenker and Roberts 2009; Annan and Schlenker 2015; Burke and Emerick 2016). The piecewise linear approach, following Schlenker and Roberts (2009) and Burke and Emerick (2016), allows us to identify the effects of both a risk of water deficit and a risk of excess water on farmers' cropping patterns and insurance take-up responses to preplant precipitation.[3] In this setting of exogenous variation in preplant precipitation, unobserved characteristics of farms and farmers

2. With Minnesota and South Dakota included, the study area would encompass a block of six contiguous states. They are not included, however, because their high-resolution cropland data do not begin until 2006.

3. Both drought and excess precipitation are frequent entries in the Causes of Loss database on crop insurance claims, which is maintained by the RMA (http://www.rma.usda.gov/data/cause.html).

may be correlated with both cropping pattern and preplant precipitation. For instance, in a semiarid area that typically experiences low precipitation as part of its climate, farmers may have adjusted in various ways (e.g., with farm machinery or tillage practices) 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-level land uses with preplant precipitation from 2001 to 2014 at a one-square-mile level, containing 640 acres. These one-square-mile blocks of farmland, called *sections*, tend to have only one or a few owners per section according to the Public Land Survey System (PLSS).[4] We employ section fixed effects in the land-use regressions, as in Holmes and Lee (2012).[5] We employ county fixed effects in the insurance take-up regressions.

Our results show heterogeneity across states in cropping-pattern adaptation to preplant precipitation from 2001 to 2007.[6] Farmers in North Dakota and Nebraska are much more responsive than those in Iowa and Illinois. When preplant 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. In Illinois, although farmers are less responsive, the adaptation effects are nevertheless statistically significant for their three crops (corn, soybeans, and grassland). Iowa appears to combine the ideal climatic and soil conditions for growing corn and soybeans such that they are optimal choices under a wide range of preplant precipitation conditions.

During the SURE regime from 2009 to 2011, farmers in all four states changed cropping patterns in response to SURE's reduced deductibles. Farmers in North Dakota and Nebraska planted more acres in corn and fewer acres in wheat, soybeans, and grassland crops when facing extreme preplant precipitation. Although less responsive in magnitude, statistically significant effects were also found for corn and soybeans in Illinois and Iowa. Moral hazard under the SURE program provides a clear explanation for this risk-taking in cropping pattern. Farmers apparently were substituting crop insurance for adaptation as a means of managing risk.

Notably, after the program's termination from 2012 to 2014, farmers largely reversed course, returning cropping patterns close to the original, preprogram patterns of 2001 to 2007.

4. 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 a quarter section as the analytical unit because it does not cover all parts of North Dakota and Iowa.

5. In addition to accounting for unobserved heterogeneity at a fine scale, using the section as the spatial unit of analysis takes advantage of high-resolution weather data, thus avoiding the problem of generating aggregated precipitation variables with relatively small variation. We discuss this further in the "Data" subsection in section 3.3.

6. We omit data from 2008 in generating the main results, as there is some ambiguity about whether the SURE program was operating prior to the March 15 deadline for crop insurance decisions in 2008.

We find limited evidence of selection on moral hazard in expenditures on crop insurance premiums in response to preplant precipitation. In both Iowa and Illinois, the SURE treatment effects for both corn insurance premiums and corn acres have the same sign and (in seven of eight cases) are highly statistically significant. That is, farmers are increasing (decreasing) insurance expenditures on corn when they increase (decrease) corn acres. The results for expenditures on soybean insurance premiums in both Iowa and Illinois are somewhat weaker, as they follow soybeans acres in sign and significance on one side of the precipitation thresholds, but not both sides, in the piecewise linear regressions. Precipitation varies more spatially than does temperature such that the use of county-level data on preplant precipitation in the insurance regressions may explain these few differences across the acreage and insurance results. Insurance regressions are not estimated for Nebraska and North Dakota, as the crop insurance data are problematic for those states.[7]

Our chapter is related to three strands of literature: adaptation to weather variation and climate change, risk-taking behavior as a moral hazard of insurance, and selection on moral hazard in insurance coverage. A growing literature addresses adaptation to climate change by economic agents in various sectors—for example, agriculture, energy consumption, and human health.[8] As in our chapter, most of this research uses historical data to estimate the impact of extreme weather as a basis to understand prospective adaptation to future climate change. In the agricultural sector, negative effects on crop yields are caused by extreme heat during the growing season (Schlenker and Roberts 2009), drought (Lobell et al. 2014), and extremely wet planting conditions (Urban et al. 2015). Our study differs in three regards: (i) it examines cropping patterns as a mechanism of adaptation[9] instead of crop yield as an outcome of adaptation; (ii) it focuses on an intermediate-run production perspective by analyzing the cropping pattern decision, in contrast to the very-short-run (growing season) and short-run (planting-growing season) perspectives of the aforementioned studies; and (iii) it uses high-resolution spatial data on land use and weather instead of relying solely on county-level data.

Our chapter is also related to the extensive empirical literature on moral

7. Annan and Schlenker (2015) describe these problems with the crop insurance data. We discuss this in more detail in the "Data" subsection in section 3.3.

8. Related literature includes Deschênes and Greenstone (2007); Schlenker and Roberts (2009); Fisher et al. (2012); and Urban et al. (2015) on agriculture; Davis and Gertler (2015) and Mansur et al. (2008) on energy consumption; and Barreca et al. (2016) and Deschênes and Greenstone (2011) on human health.

9. Our research is similar to that of Kala (2017), Khanal et al. (2017), Miller (2014), and Rosenzweig and Udry (2014), all of whom study farmer adaptation to expected precipitation during the growing season in the context of developing economies. Our research also relates to recent studies that conduct randomized controlled trials to elicit the effect of rainfall insurance programs on farmers' response to weather risk (Cole et al. 2017; Karlan et al. 2014; Mobarak and Rosenzweig 2014). Our results are consistent with their findings that a risk-management program induces farmers to switch to production of riskier crops.

hazard in insurance markets (see, for example, Einav, Finkelstein, and Levin 2010; Finkelstein 2015). In the agricultural sector, Weber, Key, and O'Donoghue (2016) review research related to moral hazard in the crop insurance market. Two studies reach contrary conclusions on the topic. Weber, Key, and O'Donoghue (2016) find no evidence of moral hazard with respect to crop productivity, crop specialization, and input use, while Roberts, O'Donoghue, and Key (2014) find such evidence with respect to crop yield. Deryugina and Kirwan (2018) find that expectations of agricultural disaster aid affect the crop insurance decision, a type of moral hazard. Our study is most similar to that of Annan and Schlenker (2015), who are the first to connect the two topics of adaptation to weather and moral hazard in insurance. They find that crop insurance gives farmers a disincentive to reduce damage to crop yields from extreme heat. Insurance thus perversely makes farmers less responsive to the weather (moral hazard).

A key feature of our chapter is the study of moral hazard's hidden action—for instance, planting corn after experiencing extreme preplant precipitation—instead of the outcome of the hidden action. Other research, in contrast, commonly assesses an outcome of the action instead of the action itself. For example, Einav et al. (2013) study the response in health insurance utilization to increased insurance coverage as a form of moral hazard; they do not study individuals' efforts in maintaining their health.[10] Similarly, Annan and Schlenker (2015) examine the effect of crop insurance coverage on crop yield; they do not study farmers' reduction in input use as the mechanism for explaining lower yield.[11] In our case, data on preplant precipitation are not recorded in an insurance contract. Thus the choice of which crop to grow, conditional on preplant precipitation, is not observed by the insurance company. From the vantage point of the analyst, our unique data set translates this choice from unobservable to observable at a high degree of spatial resolution in the PLSS section.

Lastly, our chapter is related to research by Einav et al. (2013), who conduct the first study of selection on moral hazard. Moral hazard and adverse selection are conventionally analyzed as distinct phenomena of insurance markets, but Einav et al. connect the two by investigating an individual's

10. Einav et al. (2013) write of the "abuse of terminology" related to the notion of "moral hazard" used in the literature on health insurance. They note that "moral hazard" should refer to a hidden action that would affect an individual's health status. Beginning with Arrow (1963), however, "moral hazard" has instead referred to the responsiveness of health-care spending to insurance coverage. Only by assumption does health-care spending relate directly to health status and moral-hazard behavior. In this general context, Einav et al. (2013) follow convention by defining "moral hazard" as the price elasticity of demand for health care rather than as a hidden action that would affect health status.

11. Annan and Schlenker (2015) argue that an increase in insurance coverage caused a decrease in yield as a consequence of unobserved moral-hazard behavior. They rule out, albeit indirectly, that the lower yield is due to insuring lower-quality land through the crop insurance market.

selection of insurance coverage dependent on the expected behavioral response to the coverage. Here we complement our focus on moral hazard in cropping pattern by examining the effect of preplant precipitation on crop insurance take-up—that is, whether crop insurance coverage shifts in response to SURE's reduced deductibles in the same way as cropping pattern. This is a new perspective on adverse selection in the crop insurance market. Adverse selection is no longer considered to be a major concern in this market due to risk adjustment in contract pricing—that is, setting insurance premiums based on farm-level data on historical crop yields and insurance claims (Du, Feng, and Hennessy 2017).[12] Our research reconsiders the possibility of adverse selection in crop insurance based on asymmetric information about how preplant precipitation affects cropping pattern. In doing so, we follow Einav et al.'s (2013) recommendation for research into selection on moral hazard in a context other than health insurance.

The interdependent topics of adaptation, moral hazard, and selection on moral hazard relate to significant public policy issues. Understanding farmers' adaptation to weather risk is essential for designing government programs to efficiently deal with the risk (Mendelsohn 2000). The importance and cost of these programs might only increase given that episodes of extreme weather are likely to increase under a changing climate.

The rest of the chapter proceeds as follows: Section 3.2 describes the relevant background. Section 3.3 describes the empirical strategy and data. Section 3.4 reports preliminary material on the effect of preplant precipitation on crop yields—this sets the stage for the main results. Section 3.5 presents the main regression results on land use, including adaptation and moral hazard in response to preplant precipitation. Section 3.6 presents the main regression results on crop insurance take-up and how it relates to land use—that is, selection on moral hazard. Section 3.7 describes robustness checks on the land-use results. Section 3.8 offers concluding remarks.

3.2 Background

3.2.1 Precipitation and Crop Growth in the Midwest

Crops need water to grow. The amount of water available for crop growth in rain-fed agriculture depends on the interaction between precipitation and the water-holding capacity of soil. In 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, Wang, and

12. Risk adjustment—the standard approach to mitigating adverse selection—is executed by setting insurance premiums based on observable characteristics of the buyer that predict his or her insurance claims (Einav et al. 2013).

Zhao (2012) compare the sensitivity of crop growth to water input and report that corn's average sensitivity to water is greater than the sensitivity of other major crops in the region (soybeans, wheat, and alfalfa). Thus when farmers expect extreme precipitation, they may substitute other crops for corn.[13]

Precipitation both prior to the growing season and during the growing season is important for crop growth, as this total supply provides the water to crops. Relative to growing-season precipitation, preplant precipitation provides three distinct influences on farmers' cropping pattern decisions. First, preplant precipitation can affect root growth. Precipitation from October through April is important in this region for recharging soil moisture. By recharging soil, preplant precipitation is then available as water to enhance root growth during the growing season (Neild and Newman 1990).

Second, preplant precipitation can affect crop growth through indirect mechanisms. For example, Iowa experienced exceptionally warm winters in 2011 and 2012. The resulting lower preplant 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 preplant precipitation can increase the risk of seedling diseases. Farmers may extend the planting period in response to excess preplant precipitation, but this increases the risk of foregoing yield in the late summer (Steduto et al. 2012; Urban et al. 2015).

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

3.2.2 Crop Insurance

Since the 1980s, the US 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 assist 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).[14] To increase participation rates, subsidy provisions for crop insurance thus were included

13. In table 2 of Anderson, Wang, and Zhao (2012), the index of water-use efficiency (WUE) is compared across major US crops. The WUE index is a proxy for a crop's average sensitivity to water. The index for corn is set at 1.0 as a benchmark. The indexes of other major crops in our study region are as follows: 0.65 for soybeans, 0.71 for wheat, and 0.43 for alfalfa. The smaller values indicate that, relative to corn, growth of these crops is less sensitive to water input.

14. Deryugina and Kirwan (2018) examine the relationship between crop insurance and disaster payments. They find that expected disaster payments affect producers' crop-insurance decisions.

in major legislative programs in 1980, 1994, and 2000, with the expectation of reducing reliance on disaster payments (Shields and Chite 2010).

The crop insurance market blends private incentives and government intervention.[15] On the demand side, farmers purchase insurance by crop and pay premiums adjusted to their own historical crop yields and insurance claims. Farmers select either yield-based insurance or revenue-based insurance, where the latter includes both yield and crop price provisions. Farmers also select coverage levels. These range in five-unit intervals from 55 percent to 85 percent, and in some regions only to 75 percent, for yield coverage and the yield provision of revenue-based insurance. The percentages are relative to a benchmark of 100 percent of the farm's historical average yield of the crop. For the price provision, coverage levels range in five-unit intervals from 60 percent to 100 percent. These percentages are relative to a 100 percent benchmark set by the expected market price, as determined on futures markets. A larger coverage level naturally translates into a higher premium for insuring a given acreage of a crop. A larger coverage level also translates into a smaller deductible—that is, the deductible equals 100 percent minus the coverage percent.

Here we study the demand side of crop insurance using expenditures on premiums as the outcome variable. In 2014, farmers paid $3.79 billion in premiums to insure 294 million acres of crops (Shields 2015). Nationally, this covered the vast majority of planted acreage of corn (87 percent), soybeans (88 percent), and wheat (84 percent).

The supply side of the crop insurance market relies on private insurance companies operating with substantial government intervention. Nineteen companies sell crop insurance to farmers, yet they function under the purview of USDA's Risk Management Agency (RMA) and its Federal Crop Insurance Corporation (FCIC). The FCIC strictly limits the type of policies that can be sold, and it derives formulas for premium rates that are developed in the context of the federal government's subsidy provisions. In 2014, the crop-insurance subsidy totaled $6.27 billion. Thus the farmer-paid premiums of $3.79 billion (38 percent) plus the $6.27 billion in subsidy (62 percent) equaled the gross insurance premiums, $10.06 billion. Both private and public expenditures on crop insurance are substantial.

3.2.3 The Supplemental Revenue Assistance Payments Program

The crop insurance program, by the mid-2000s, had failed to replace disaster payments despite substantial growth in its participation rates.[16] To

15. Shields (2015) provides an excellent introduction to crop insurance, including its type of products, institutional setting, and historical experience in the United States. We rely on this for many of the details here.

16. The US Congress continued to establish ad hoc disaster assistance primarily through emergency supplemental appropriations. Thirty-nine acts established disaster payments to farmers between 1989 and 2007, and such payments were provided every year during this period (Chite 2010).

further promote crop insurance, the US Congress authorized a new program in the 2008 Farm Bill, the SURE program (Shields 2010). The SURE program supplemented crop insurance by compensating producers for so-called shallow losses—that is, losses that were part of a policy's deductible. To be eligible for a SURE payment, a farmer needed to purchase insurance on all planted crops. Then to qualify for a payment, the farm (i) had to be located in a federally declared disaster county or a county bordering a disaster county or (ii) had to suffer a crop loss that exceeded 50 percent of expected yield. In its formula, the SURE payment increased with the farmer's insured coverage level.

Previous research has argued that the SURE program was likely to encourage moral hazard in farmer decision-making by both reducing the deductible at which payments began and converting to a whole-farm revenue approach. First, SURE payments were initiated when a crop suffered a yield loss of 10 percent or more—that is, farmers could insure 90 percent of their expected yield when SURE payments were combined with insurance indemnities (Glauber 2013; Smith and Watts 2010). This contrasts with the typical maximum of 85 percent coverage of expected yield under crop insurance. This substantial reduction of deductibles under SURE created incentives for risk-taking in crop choice and production. Empirically, Bekkerman, Smith, and Watts (2012) find that the SURE program markedly increased insurance participation rates, measured by the ratio of net insured acres to total planted acres at the county level.

Second, SURE payments were based on a whole-farm revenue approach, whereas prior to 2008, payments were based on crop-specific losses. 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). Growing a single crop might increase the chance that a farm would drop below its guaranteed revenue threshold at which program payments were triggered. Therefore, changes in crop-choice decisions could be evidence of response to the program's incentives.

Payments to farmers were substantial under the SURE program. Bekkerman, Smith, and Watts (2012) report that \$2.11 billion in SURE payments were made for low production in 2008, which is about five times higher than the Congressional Budget Office's original estimated annual payments under the program, \$425 million (CBO 2011). The US Government Accountability Office reports total SURE payments of \$2.52 billion for fiscal years 2008 to 2012 (USGAO 2014).

The SURE program ran for only a short time, 2008 through 2011. The program's timeline suggests that farmers did not make 2008 planting decisions with information about the program. At the same time, farmers later received SURE payments for 2008 crop losses. We excluded 2008 from the main analysis because of this ambiguity about program timing relative to farmer decision-making.

3.3 Empirical Strategy

This section includes three parts: a simple conceptual motivation of land-use and insurance decision-making under weather risk; description of the econometric models for studying land use, insurance take-up, and crop yield; and description of the data.

3.3.1 Conceptual Motivation

We motivate the econometric analysis of land use and insurance take-up with a simple stylized example that considers farmer decision-making faced with growing-season weather risk. It begins with conditions prior to the SURE program and continues with an extension to the SURE program. For the sake of illustration, we consider a farmer's choice to plant wheat or corn on a North Dakota farm.

Pre-SURE program. March 15 is the deadline for purchasing 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 preplant precipitation on March 15. Preplant 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 preplant precipitation is relatively low on March 15, and this signal creates conditional probabilities of two precipitation outcomes for the planting and growing seasons. 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 cropland to either 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 preplant 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 preplant precipitation decreases to a level of water deficit in North Dakota. The farmer also purchases crop insurance for wheat, not corn.

SURE program. In the hypothetical, the SURE program reduces the deductible on crop insurance; farms with yield losses in the 75 percent to 90 percent range of historical yields now qualify for SURE payments. We suppose, on the farm considered here, that corn yield is below 90 percent 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 $\pi_2^{C\prime}$. With $\pi_2^{C\prime} > \pi_2^C$, we posit that corn production now generates higher expected profit than wheat, or

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

The farmer changes crops, now allocating cropland to corn, not wheat. This illustrates the moral hazard created by the SURE program: the farmer is taking a risk on corn. The farmer also purchases crop insurance for corn, not wheat. Once again extrapolating to the empirical analysis, we expect the program to increase corn acres and decrease wheat acres—relative to preprogram levels—over the range of relatively low preplant precipitation levels. In addition, we expect insurance coverage to increase on corn, reflecting selection on moral hazard. These are the type of treatment effects expected from the SURE program.

3.3.2 Piecewise Linear Regression Models

Our study area includes four major agricultural states in the Midwest: the entire states of Iowa and Illinois and the regions east of the 100th meridian in North Dakota and Nebraska that rely on rain-fed farming. The study encompasses 2001 to 2014. By beginning in 2001, we avoid the period prior to the major change in crop insurance policy (substantially increasing premium subsidies) that was enacted in 2000 with the Agricultural Risk Protection Act. We span the SURE program years, 2009 to 2011, which enables analysis of the postprogram period as part of the research design. By ending in 2014, we avoid a new supplemental insurance program that was enacted in the Agricultural Act of 2014 and implemented in 2015.

In the analysis, we exploit random year-to-year variation in preplant precipitation as a natural experiment. Preplant precipitation operates as a continuous treatment variable, with the treatment intensity varying across the observed range of preplant precipitation. In tandem with the weather experiment, we utilize the SURE program's shock to insurance deductibles as a quasi experiment. The identifying assumption of the estimation strategy for SURE treatment effects is that local preplant precipitation shocks are exogenous to the policy changes in 2009 and 2012. We find no evidence that our preplant precipitation variable and the policy changes are correlated. More generally, it is unlikely that annual preplant precipitation caused a policy change such as the SURE program or that the SURE program caused a change in preplant precipitation.

Land-use regressions. Previous research has demonstrated a strong nonlinearity in the relationship between precipitation during the growing season and crop-yield outcomes (Annan and Schlenker 2015; Burke and Emerick 2015; Schlenker and Roberts 2009). 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 preplant precipitation. 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 reenters the estimation, raising omitted variables concerns, as identification in the panel models is no longer limited to location-specific variations 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 risks—water shortage and water excess—on farmers' cropping pattern response to preplant precipitation. Our use of high-resolution spatial data on land use and weather facilitates estimation of a flexible model that can detect nonlinearities and thresholds in the effect of preplant precipitation on land allocation to crops.

We model log planted acres of a crop in section i, state s, and year t ($cropacre_{ist}$) as a piecewise linear function of preplant precipitation with a threshold (or kink) at p_0. The effect of the new SURE program in 2009 on cropping pattern adaptation to precipitation risk is identified with the interaction term between our preplant precipitation variable $prec_{\mathrm{it}}$ and a policy dummy $d09_t$ equal to 1 if the year is 2009 to 2011. Similarly, the effect of the termination of the SURE program on cropping pattern adaptation to precipitation risk is identified with the interaction term between $prec_{it}$ and a policy dummy $d12_t$ equal to 1 if the year is 2012 or later. We estimate the fixed effects model

$$(1) \quad cropacre_{ist} = \alpha + \beta_1 prec_{it;p<p_0} + \beta_2 prec_{it;p<p_0} d09_t + \beta_3 prec_{it;p<p_0} d12_t + \beta_4 prec_{it;p>p_0} + \beta_5 prec_{it;p>p_0} d09_t + \beta_6 prec_{it;p>p_0} d12_t + \gamma temp_{it} + \boldsymbol{X}\theta + \mu_i + \delta_t + g_s(t) + \epsilon_{ist},$$

where the variable $prec_{it;p<p_0}$ is the difference between preplant precipitation and p_0 interacted with an indicator variable for preplant precipitation being below the threshold p_0. $prec_{it;p>p_0}$ is similarly defined for preplant 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 preplant temperature from October 1 to March 15. $\boldsymbol{X}$ is a vector of control variables, including planting-season precipitation, temperature, and future crop price. The planting-season variables control for the fact that farmers may revise land-use decisions subsequent to March 15 based on updated weather conditions. The μ_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 (Holmes and Lee 2012). 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 crop insurance premiums and biofuel policies. Similar to Annan and Schlenker (2015), we include $g_s(t)$ as a quadratic time trend, by state, to control for trends in agricultural technologies (such as seed types or drainage capital) that might affect yields and related land-use decisions.

The parameters of interest are the set of $\boldsymbol{\beta}$. β_1 and β_4 provide estimates of how farmers' crop acreage decisions respond to preplant precipitation prior to the SURE program both below and above the threshold, respectively; these parameters estimate adaptation. β_2 and β_5 provide estimates of the SURE treatment effects, or how farmers *change* their response to preplant precipitation under the SURE program; these parameters estimate moral hazard. Hence $\beta_1 + \beta_2$ and $\beta_4 + \beta_5$ provide estimates of how farmers respond to preplant 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 the SURE program relative to during the program. $\beta_1 + \beta_2 + \beta_3$ and $\beta_4 + \beta_5 + \beta_6$ provide estimates of how farmers respond to preplant precipitation after the SURE program both below and above the threshold, respectively. These parameters once again estimate adaptation.

Equation (1) is estimated by crop and by state for Illinois, Iowa, Nebraska, and North Dakota.

An important note with respect to the SURE treatment effects (β_2 and β_5) is that we do not observe purchase of crop insurance at the section level. That is, when observing land use in a section, we do not know whether the crops are insured. Insurance participation rates are quite high in general, with almost 90 percent of US corn, soybean, and wheat acres covered by insurance. Nevertheless, the implication is that the estimated treatment effects are underestimates of the true effects.

Lastly, an ambiguity arises with observations from 2008. The SURE program was part of a policy enacted on May 22, 2008, so it is unlikely that farmers could have included information about the program in insurance and planting decisions by March 15 of 2008. Nevertheless, we exclude observations from 2008 from our main analysis and then include them in the preprogram period in a robustness check.

Insurance take-up regressions. We estimate crop insurance take-up using the same structure of a piecewise linear function. We model log insurance premiums per planted acre of a crop in county c, state s, and year t ($premiums_{cst}$) as a piecewise linear function of total preplant precipitation with a threshold at p_0. Here we apply the actual value of the threshold p_0 from the land-use regression as a way to gauge whether the SURE treatment effect on insurance take-up follows the SURE treatment effect on land use (selection on moral hazard). We estimate the fixed effects model

$$(2)\quad premiums_{cst} = \alpha + \beta_1 prec_{ct;p<p_0} + \beta_2 prec_{ct;p<p_0} d09_t + \beta_3 prec_{ct;p<p_0} d12_t + \beta_4 prec_{ct;p>p_0} + \beta_5 prec_{ct;p>p_0} d09_t + \beta_6 prec_{ct;p>p_0} d12_t + \gamma temp_{ct} + \boldsymbol{X}\theta + \mu_c + \delta_t + g_s(t) + \epsilon_{cst},$$

where μ_c are county fixed effects that control for unobserved time-invariant characteristics that affect insurance take-up, such as expected disaster payments in the county or the historical probability of a county being declared a disaster county. Other variables are defined as in equation (1).

The outcome variable in each insurance regression is specified as a rate, premiums divided by total planted acres, and not simply premiums.[17] To demonstrate selection on moral hazard, farmers need to purchase better insurance coverage when, for example, they are increasing acreage in a crop after being treated with the SURE program. With the county-level data, this requires showing increases in insurance coverage per acre of a crop—that is, the rate of insurance must be increasing. Thus the parameters of interest are the SURE treatment effects, β_2 and β_5, and how they compare with the respective β_2 and β_5 for a particular crop from the land-use regressions.

Equation (2) is estimated for corn and soybean insurance premiums by state for Illinois and Iowa.

Crop yield regressions. We estimate crop yield regressions while once again using the same structure of a piecewise linear function. We model log crop yield in county c, state s, and year t ($cropyld_{cst}$) as a piecewise linear function of preplant precipitation with a threshold at p_0. We estimate the fixed effects model

$$(3)\quad cropyld_{cst} = \alpha + \beta_1 prec_{ct;p<p_0} + \beta_2 prec_{ct;p<p_0} d09_t + \beta_3 prec_{ct;p<p_0} d12_t + \beta_4 prec_{ct;p>p_0} + \beta_5 prec_{ct;p>p_0} d09_t + \beta_6 prec_{ct;p>p_0} d12_t + \gamma temp_{ct} + \boldsymbol{X}\theta + \mu_c + \delta_t + g_s(t) + \epsilon_{cst},$$

where $\boldsymbol{X}$ is a vector of variables for weather during the planting and growing seasons that serve as controls. We allow the data to determine p_0 by looping

17. Deryugina and Kirwan (2018) use premiums as their outcome variable, arguing that it captures both the intensive margin (choice of a discrete coverage level) and extensive margin (insured acres) of crop insurance. Annan and Schlenker (2015) use the rate of insurance, insured acres divided by total planted acres.

over all possible thresholds and selecting the model with the lowest sum of squared residuals. Other variables are defined as in equations (1) and (2).

Equation (3) is estimated for corn and soybean yields using data pooled across Illinois, Iowa, and eastern North Dakota. Once again, the parameters of interest are the set of β, and they are interpreted in a similar way as the β in equation (1). These parameters show the estimated effects of preplant precipitation on crop yields.

3.3.3 Data

The unit of analysis for studying land use is the PLSS section, which is a 1 × 1 mile square piece of land. We use a geographic information system (GIS) data layer to define sections (ESRI 2015). By state, the number of sections is as follows: Illinois, 45,372; Iowa, 50,020; Nebraska, 14,426; and North Dakota, 27,151 (table 3.1). Sections in eastern North Dakota and eastern Nebraska with irrigated land are excluded.[18] Following Schlenker et al. (2005), the analysis focuses solely on rain-fed farming.

The unit of analysis for studying insurance take-up and crop yield is the county. By state, the number of counties is as follows: Illinois, 102; Iowa, 99; and North Dakota, 28. The county-level statistical analysis excludes eastern Nebraska because of its preponderance of irrigated agriculture; almost two-thirds of PLSS sections in eastern Nebraska rely on irrigation.

Land-use data. The land-use data are from the National Agricultural Statistics Service (NASS)'s Cropland Data Layer (CDL) program, which provides high-resolution geospatial data on crops planted and other types of land cover for the United States.[19] For the four states, we constructed a balanced panel of planted acres by crop within the 640 acre PLSS sections from 2001 to 2014 (2002 to 2014 for Nebraska). The section-level data are generated by summing over the CDL grids within each section.

Table 3.1 presents summary statistics for mean acreage by state for corn, soybeans, spring wheat, and grassland, averaged over the sections and study 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. Grassland is a single land-cover category, not a crop. 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* category.

18. Data on the sections with irrigated agriculture are from the 250-meter scale irrigation map in 2007 from the Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US). See Brown and Pervez (2014) for documentation.

19. Donaldson and Storeygard (2016) highlight the CDL as an example of high-resolution satellite data with promising potential for application in economics.

Table 3.1 **Summary statistics**

		North Dakota			Iowa		
	Unit	Mean	Median	Std. dev.	Mean	Median	Std. dev.
Panel (A): Section-level variables for land-use regressions							
Corn acreage[a]	acre	49.51	6.75	88.29	222.85	222.30	134.61
Soybean acreage[a]	acre	118.74	71.10	132.80	170.63	162.23	116.05
Spring wheat acreage[a]	acre	110.49	72.13	120.68	0.10	0	1.79
Grassland acreage[a]	acre	196.52	149.85	172.58	151.82	111.83	131.21
Preplant precipitation[b]	mm	127.99	122.04	47.49	226.37	218.53	67.36
Preplant temperature[b]	°C	–6.19	–6.55	2.24	–0.65	–0.68	2.13
Planting precipitation[b]	mm	152.07	148.41	47.01	251.71	240.75	70.17
Planting temperature[b]	°C	7.12	7.43	2.21	11.04	11.03	1.85
Sections			27,151			50,020	
Observations			352,963			650,260	
		Illinois			Nebraska		
Corn acreage[a]	acre	194.71	181.10	146.88	68.95	9.68	99.23
Soybean acreage[a]	acre	157.77	145.13	119.55	55.51	1.35	90.68
Spring wheat acreage[a]	acre	0	0	0.30	0.01	0	0.51
Grassland acreage[a]	acre	102.67	74.70	97.40	433.52	501.76	199.43
Preplant precipitation[b]	mm	380.52	360.06	108.55	156.29	145.84	52.11
Preplant temperature[b]	°C	2.74	2.77	2.28	0.70	0.77	1.68
Planting precipitation[b]	mm	264.72	248.42	93.95	203.47	198.75	73.84
Planting temperature[b]	°C	13.31	13.35	1.97	11.29	11.22	1.87
Sections			45,372			14,426	
Observations			589,836			173,112	
		Iowa			Illinois[f]		
Panel (B): County-level variables for insurance demand regressions							
Corn insurance premiums[d]	1,000 $	3,982	3,361	2,625	3,567	2,589	3,223
Soybean insurance premiums[d]	1,000 $	1,814	1,591	1,153	1,558	1,217	1,281
Corn premiums per acre[e]	$/acre	31.05	29.44	17.10	29.79	28.79	17.93
Soybean premiums per acre[e]	$/acre	18.94	16.94	10.31	17.16	15.67	11.15
Preplant precipitation[b]	mm	226.93	218.50	67.57	389.16	366.63	114.88
Preplant temperature[b]	°C	–0.36	–0.37	2.18	3.17	3.20	2.37
Planting precipitation[b]	mm	252.08	240.06	69.65	267.56	250.42	96.31
Planting temperature[b]	°C	11.67	11.64	1.89	14.04	14.10	2.03
Counties			99			102	
Observations			1,287			1,291	

[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 the appendix for our calculation of weighted land capability at the section level.

[d] Authors' calculations with the Risk Management Agency's Summary of Business Reports and Data, 2001–2014.

[e] Premiums divided by planted acres by crop. Data on planted acres are from the National Agricultural Statistics Service.

[f] The number of observations for corn in Illinois is 1,285. Summary statistics of preplant and planting precipitation and temperature for the sample of corn in Illinois are very similar to the values reported here using the 1,291 observations from the soybean sample in Illinois.

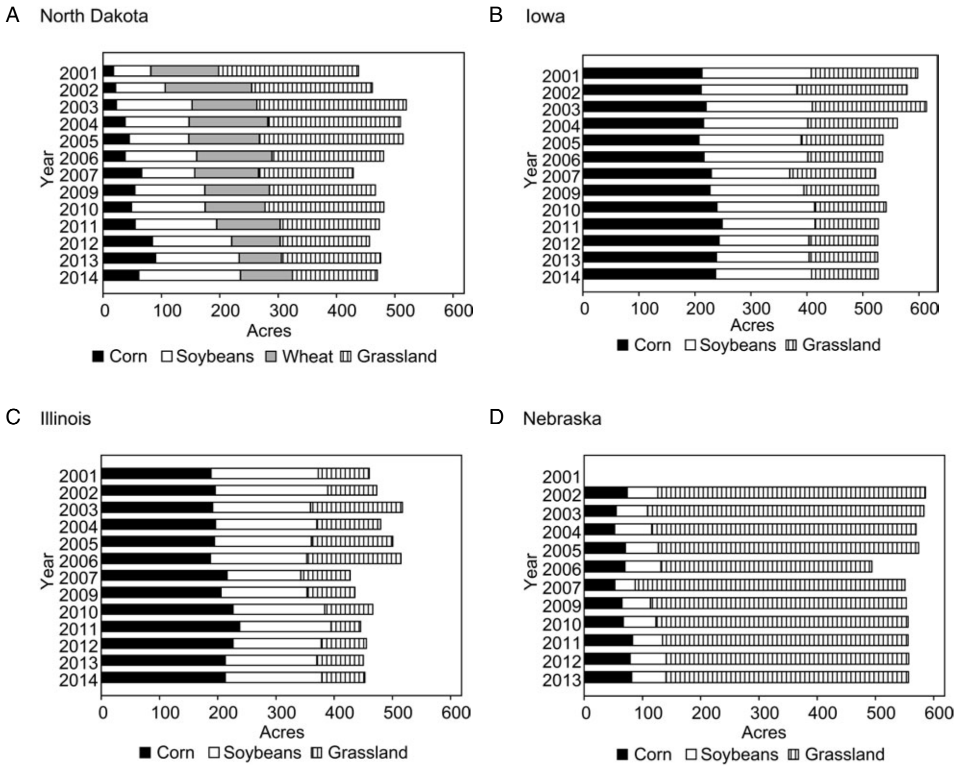

Fig. 3.1 Average cropland and grassland acres at the section level

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 nonirrigated PLSS sections.

Figure 3.1 displays 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 to 2011, which are larger than those before 2008. The differences could be driven by the price effects of biofuel policy, which we control for with year 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.

Weather data (section level). The weather data are an updated version of those used in Schlenker and Roberts (2009), which consist of daily precipitation and maximum and minimum temperatures at 4 × 4 kilometer grid cells in the United States from 1950 to 2014. For each cell, preplant precipitation is the accumulated precipitation from October 1 in the previous year to March 15 in the current year—that is, precipitation from the end of the previous growing season through the deadline for purchasing crop insurance. Preplant temperature is computed by averaging daily average temperature over the same period. Planting-season precipitation is the accumulated precipitation from March 16 to May 31 for Iowa, Illinois, and Nebraska and from March 15 to June 15 for North Dakota. Planting-season temperature is the average of daily temperatures over these same periods. To match the spatial delineation of the land-use data, these four data series are converted to the section level by averaging each series over the intersected cells.

Using the section as the unit of analysis takes advantage of the high-resolution precipitation data. While temperature is a large-scale weather event, precipitation tends to be a microscale event—that is, precipitation intrinsically varies more spatially because local vegetation and geography can affect it. Use of aggregated weather data may result in small variation in precipitation variables.[20]

Mean preplant precipitations in North Dakota and Nebraska are 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 (table 3.1). Illinois also has relatively larger variation in preplant precipitation. Using the raw data, figure 3.2 presents different forms of the nonlinear relationship between preplant precipitation and corn acreage for each state during the three periods: before 2008, 2009 to 2011, and 2012 to 2014. In North Dakota, for example, relatively low preplant precipitation occurred from 2001 to 2007 and after 2012, while relatively high preplant precipitation occurred from 2009 to 2011, as can be seen in panel (A). In Illinois and Iowa, figure 3.2 shows that the relationships between preplant precipitation and corn acreage are somewhat similar across the three periods. In North Dakota and Nebraska, in contrast, the relationships between preplant precipitation and corn acreage from 2009 to 2011 appear very different from those during the other two periods.

One concern with the land-use regressions is that the section and year fixed effects can absorb a significant amount of the variation in the preplant precipitation variables (Fisher et al. 2012). Following Fisher et al. (2012), we explore how much of the variation is absorbed by the fixed effects. The appendix reports results showing that substantial residual variation exists to implement our approach (table 3A.2). This conclusion is reinforced by the standard errors on the various estimated coefficients on the preplant precipitation variable in the (subsequent) land-use regressions.

Weather data (county level). We also use the same raw data to produce county-level weather data for the crop insurance regressions and the yield

20. Mearns et al. (2001) and Fezzi and Bateman (2015) show that 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.

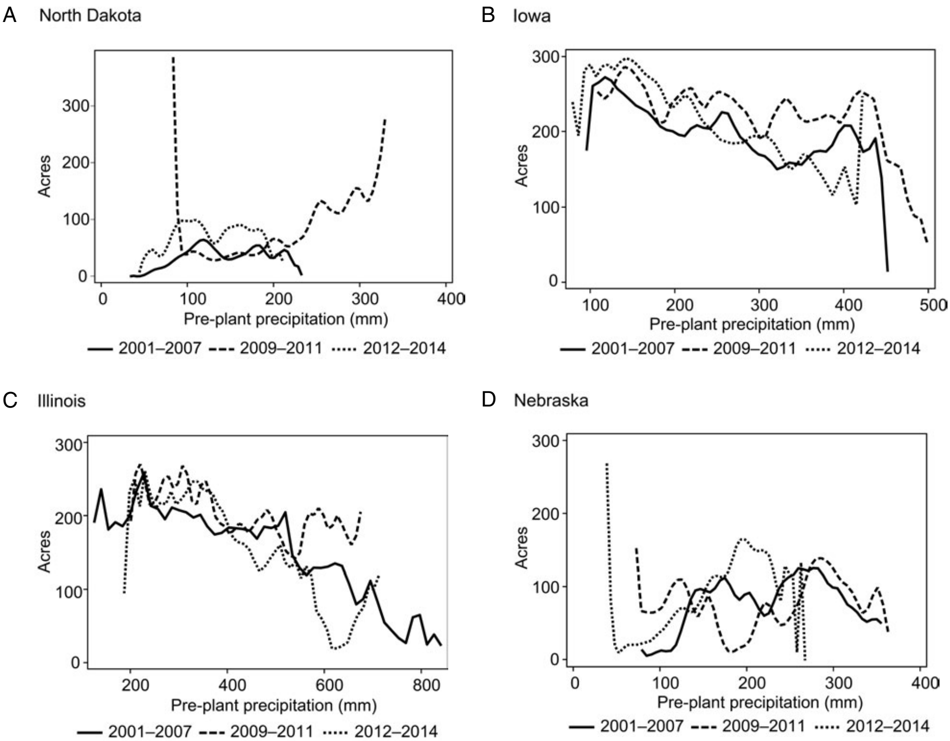

Fig. 3.2 Relationship between corn acres and preplant precipitation

Notes: These plots are generated by kernel-weighted local polynomial smoothing with the following 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 nonirrigated PLSS sections. Preplant precipitation is in millimeters.

regressions. For the crop insurance regressions, the four county-level weather variables are preplant precipitation, preplant temperature, planting-season precipitation, and planting-season temperature. Their summary statistics are reported for the states with insurance regressions, Illinois and Iowa (table 3.1).

County-level weather data are also produced for the yield regressions for the relevant states: Illinois, Iowa, and eastern North Dakota. Seven variables are developed: preplant precipitation, preplant temperature, planting-season precipitation, planting-season temperature, growing-season precipitation, growing-season temperature, and the daily maximum temperatures during July. Summary statistics for the three-state region are reported in the appendix (table 3A.3).

Insurance data. County-level administrative data on insurance premiums are from the RMA. We use the dollar value of premiums paid by farmers.[21] These data cover corn and soybeans in Illinois and Iowa. Our dependent variable in the insurance regressions is premiums divided by total planted acres of the respective crop, or dollars per acre. County-level data on total planted acres are from the NASS. Summary statistics are reported in table 3.1.

We exclude North Dakota from the state-based analysis of insurance premiums. With only 28 counties, eastern North Dakota presents challenges for obtaining accurate regression estimates. More important, the crop insurance data are of questionable quality in North Dakota. The data were first questioned by Annan and Schlenker (2015), who were concerned with data on total planted acres. To understand this further, we display data on insured acres from RMA versus planted acres from NASS (figure 3.3). Beginning in 2008 and continuing through 2014, the number of insured acres equaled and, in several years, greatly exceeded planted acres for corn and soybeans in the state. For this reason, we do not estimate insurance take-up regressions for the crops in North Dakota.[22]

Futures price data. National data on futures prices for corn, soybeans, and wheat are from the RMA. They represent monthly average prices for February of the current growing season. These are the prices used in the formulas for revenue-based insurance of these respective crops. Thus futures price variables may help explain both land-use and insurance decisions.

Yield data. County-level data on crop yields of corn and soybeans in bushels per acre are from the NASS. Summary statistics are reported in the appendix for the study region of Illinois, Iowa, and eastern North Dakota (table 3A.3). Wheat yield is not studied, as wheat is not one of our crops in Illinois and Iowa. Similarly, grassland is not studied; grassland is an amalgamation of land covers and so does not have related yield data.

3.4 Preliminary Considerations: Does Preplant Precipitation Affect Crop Yield?

We begin with preliminary analysis that examines the effect of preplant precipitation on crop yields. The intent is to establish that preplant precipitation affects crop yields—that is, that there is an empirical justification for farmers to include preplant precipitation in decision-making. We pool the county-level data from 2001 to 2014 across three states: Illinois, Iowa, and North Dakota (with North Dakota limited to counties in the eastern part

21. Premiums paid by farmers are relevant for decision-making, while the premium subsidy paid by the federal government is not.

22. The difference between planted acres and insured acres could be explained by "acres prevented from planting" before the planting deadline under the crop insurance program. Additional research on this topic is needed to understand the incentive that crop insurance provides not to plant acres and how that interacts with preplant weather.

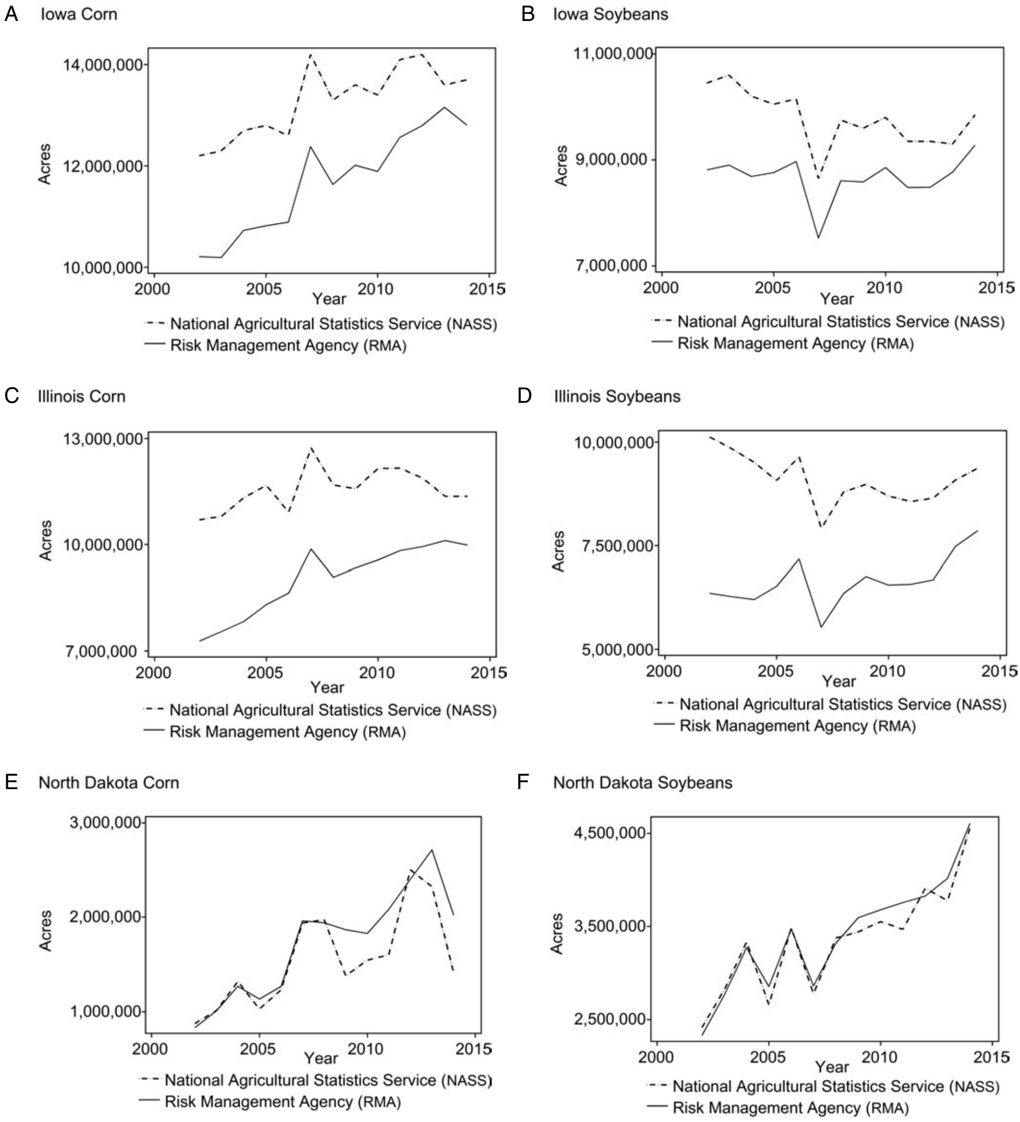

Fig. 3.3 Comparison of planted acres (NASS) and insured acres (RMA)

Notes: The graphs display planted acres and insured acres for corn and soybeans across years by state. Planted acres are data from the NASS. Insured acres are data from the RMA's Summary of Business Reports and Data. Data for North Dakota only include 28 counties east of the 100th meridian.

of the state).[23] Pooling the data across states is appropriate with yield regressions.[24] We apply equation (3) to estimate piecewise linear regressions for corn yield and soybean yield, using the common structure in our approach to assessing effects before, during, and after the SURE program. In addition to preplant precipitation and preplant temperature, other weather variables (just described) are included as controls. The appendix describes the variables and full results in more detail.

The results show that preplant precipitation affects crop yields with small but significant effects in most cases. Begin with corn yields (table 3A.4 and figure 3A.2). Below the precipitation threshold, the effect of preplant precipitation is positive and highly significant in the pre-SURE phase from 2001 to 2007 and positive but insignificant in the post-SURE phase from 2011 to 2014. Above the threshold, preplant precipitation exerts negative and highly significant effects in both the pre- and post-SURE phases.

Turn next to soybean yields. Below the precipitation threshold, the effect of preplant precipitation is negative and highly significant in the pre-SURE phase and negative but insignificant in the post-SURE phase. Above the threshold, preplant precipitation exerts negative and significant effects in both the pre- and post-SURE phases.

With the SURE program, the respective *changes* in corn yields and soybean yields are positive, with three of four estimated coefficients highly significant on variables that interact the SURE program with preplant precipitation (table 3A.4 and figure 3A.2). This is interesting per se, as it counters intuition that risk-taking during the SURE program will lead to productivity losses. In a separate study, we are investigating soil quality as a possible mechanism to explain this. Farmers might have grown corn and soybeans on land with higher-quality soil during the SURE program.

To summarize: the two yield regressions provide empirical support for the idea that farmers consider preplant precipitation in land-use and insurance take-up decision-making.

23. We exclude our study counties in Nebraska from the analysis of crop yields due to the high rate of irrigation in eastern Nebraska. In these counties, 63.4 percent of the sections are in irrigated agriculture and 36.6 percent are in rain-fed agriculture. This preponderance of irrigation skews the county-level data on crop yields.

24. Pooling the data across states is appropriate with yield regressions but not land-use regressions. With land use, individual farms typically grow more than one crop each season, and multiple crops are competing to be selected for planting in any given field. This competition can vary across states—for example, corn competes with wheat for land use in North Dakota but does not compete with wheat in Iowa. This implies a multioutput technology with tradeoffs that may differ from state to state such that state-specific regressions may be warranted. Yield, in contrast, implies a single-output technology that depends primarily on agronomic considerations in the short run such that pooling data across states is defensible. Empirically, several studies apply data pooled across states when examining the effect of extreme weather on crop yield (e.g., Schlenker and Roberts 2009; Lobell et al. 2014; Urban et al. 2015).

3.5 Results I: Adaptation and Moral Hazard in Land Use

Results from the land-use regressions (equation (1)) are reported in three subsections. The first discusses the main estimation results for a single crop, corn, which is recognized as a water-sensitive crop, and a major crop, in the Midwest. The second discusses results for a single state, North Dakota, which has a diversity of crops and land allocations. The third discusses results for the other three crops and states.

Prior to reporting results, we first explain why we do not pool the data and estimate a single regression for each crop that encompasses the four states. After all, the section fixed effects account for several time-invariant unobservables at the section level, such as soil quality, climate factors, and farm management skills. But our focus on cropping pattern—and the various crop substitutions that result in substantially different acres allocated to a particular crop across states—provides one rationale for the state-level analysis. We can observe this heterogeneity in the average cropland allocations in a section and how those allocations vary across states (figure 3.1).

A second factor favoring state-level regressions is the heterogeneity across states in preplant precipitation thresholds. In the piecewise linear approach, we allow the data for a state to determine each crop's threshold by looping over all possible thresholds based on equation (1) and then selecting the model with the lowest sum of squared residuals. As an example, the thresholds of preplant precipitation for corn vary widely across states: 100 mm in North Dakota, 370 mm in Iowa, 395 mm in Illinois, and 135 mm in Nebraska (table 3.2). With different thresholds, the piecewise linear functions vary substantially across states. Figure 3.4 illustrates this using the regression results for corn.

Overall, we estimate 13 land-use regressions for the four crops across the four states. The effects of preplant precipitation are captured in 77 estimated coefficients, with 51 of these reflecting the interaction with the SURE program and post-SURE program. Of the 77 estimates, 52 are statistically significant—that is, preplant precipitation exerts meaningful causal effects on agricultural land use.

3.5.1 The Effect of Preplant Precipitation on Corn Acres

The regression results for corn show economically and statistically significant responses to preplant precipitation in the study states (table 3.2). Farmers in states with relatively poorer natural capital in their climate and soil conditions[25] were more responsive—these are North Dakota and Nebraska. Farmers in Iowa and Illinois, in contrast, were less responsive to both pre-

25. The appendix describes data on soil quality at the section level across the four states. Illinois and Iowa have relatively high soil quality, while Nebraska has the poorest soil quality. Soil quality in North Dakota approaches that of Illinois and Iowa.

Table 3.2 **Land-use estimation results for corn**

	North Dakota (1)	Iowa (2)	Illinois (3)	Nebraska (4)
Preplant precipitation below threshold	–0.010**	–0.000	–0.000	–0.009***
	(0.004)	(0.000)	(0.000)	(0.003)
Preplant precipitation below threshold × after 2008	–0.015	–0.001**	0.001***	0.012***
	(0.041)	(0.000)	(0.000)	(0.003)
Preplant precipitation below threshold × after 2011	0.008	0.000	–0.001**	–0.006***
	(0.042)	(0.000)	(0.000)	(0.002)
Preplant precipitation above threshold	–0.006***	–0.001	–0.001***	–0.005***
	(0.002)	(0.003)	(0.000)	(0.001)
Preplant precipitation above threshold × after 2008	0.009***	0.006**	0.001	0.004***
	(0.002)	(0.003)	(0.000)	(0.001)
Preplant precipitation above threshold × after 2011	–0.010***	–0.010***	–0.001***	0.001
	(0.003)	(0.003)	(0.000)	(0.001)
Preplant temperature	–0.389**	–0.068***	0.013	–0.099*
	(0.151)	(0.023)	(0.049)	(0.056)
Preplant temperature squared	–0.019***	–0.004**	0.001	–0.015**
	(0.005)	(0.002)	(0.003)	(0.007)
Planting precipitation	–0.004	0.001	–0.000	–0.004***
	(0.003)	(0.000)	(0.001)	(0.001)
Planting precipitation squared	0.000	–0.000*	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	–0.047	0.171***	–0.000	0.019
	(0.132)	(0.035)	(0.062)	(0.087)
Planting temperature squared	0.004	–0.006***	0.004**	0.002
	(0.007)	(0.001)	(0.002)	(0.003)
Corn futures price	0.628***	0.192***	0.038	0.157***
	(0.213)	(0.034)	(0.032)	(0.042)
Observations	352,963	650,260	589,836	173,112
R-squared	0.158	0.027	0.026	0.090
Number of PLSS sections	27,151	50,020	45,372	14,426
Threshold of preplant precipitation	100	370	395	135

Notes: Dependent variable in all regressions is the log of corn acres. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include section fixed effects, year fixed effects, and a quadratic time trend by state. Regressions (1)–(4) use nonirrigated PLSS sections. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

plant precipitation and the interaction of preplant precipitation with the SURE program.

North Dakota: farmers are quite responsive to both preplant precipitation and its interaction with the SURE program. Column (1) of table 3.2 reports the results for corn in North Dakota. Before the policy change in 2009, a 1 mm decrease in preplant precipitation below the threshold decreases corn acreage by 1.0 percent, while a 1 mm increase in preplant precipitation above the threshold decreases corn acreage by 0.6 percent. The results

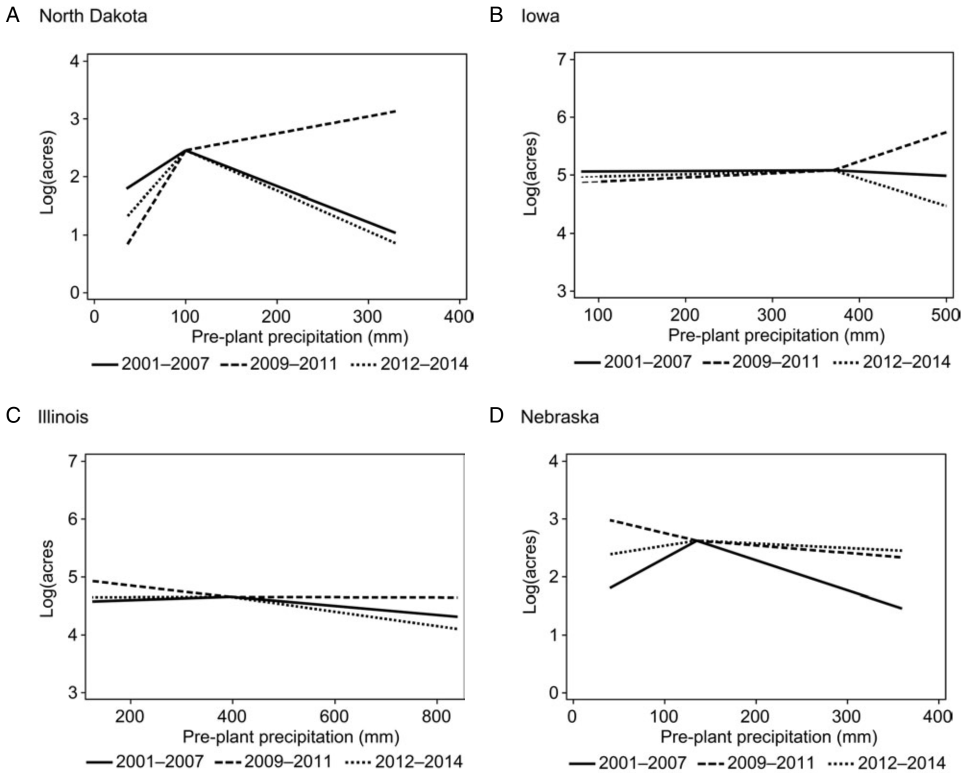

Fig. 3.4 Predicted effects of preplant precipitation on corn acres (by policy regime)

Notes: The graphs display the predicted means of log(corn acres) in the sections as a function of preplant precipitation. Panels (A)–(D) use nonirrigated PLSS sections. Preplant precipitation is in millimeters.

imply that farmers adapted to abnormal preplant precipitation by planting fewer acres in corn. This adaptation strategy was adopted even though the crop insurance program was in place. The program had created moral hazard problems even before 2009 (Roberts, O'Donoghue, and Key 2014).

Under the SURE program from 2009 to 2011, we do not obtain a statistically significant effect below the threshold, perhaps because there are relatively few observations below the threshold in North Dakota during this period. However, above the threshold, a 1 mm increase in preplant precipitation actually *increases* corn acreage by 0.3 percent, which is the sum of the coefficients −0.006 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 program's termination in 2012 only strengthen this perspective. Here a 1 mm increase in preplant precipitation *decreases* corn acreage by 0.7 percent, which is derived as the sum of −0.006, 0.009, and −0.010. Notice that the effect returns to a similar slope as before the SURE program was enacted—that is, the increase of the corn acreage function due to the new policy in 2009 was virtually offset by the decrease due to termination of the policy in 2012. This lends credibility to the interpretation of the SURE program exerting a causal effect.

Figure 3.4 illustrates the piecewise linear estimation results for North Dakota in panel (A). Before 2009, corn acreage increases linearly up to the endogenous threshold of preplant precipitation (100 mm) and then decreases linearly above that threshold; the solid line depicts this inverted-V-shaped effect. Under the SURE policy, the relationship changes substantially, as shown by the dashed line. However, after the program's termination, the relationship returns virtually to the original inverted-V-shaped effect of pre-2009; this is the dotted line in the figure.

Nebraska: farmers are responsive to preplant precipitation. Like North Dakota, farmers in Nebraska show responsiveness in corn acres as a function of preplant precipitation (column (4) of table 3.2 and panel (D) of figure 3.4). Before the policy change in 2009, a 1 mm decrease in preplant precipitation below the threshold decreases corn acreage by 0.9 percent. After the policy change in 2009, the estimated coefficient of 0.012 shows a substantial increase in corn acres such that a 1 mm decrease now increases acreage by 0.3 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 preplant precipitation below the threshold.

Above the threshold in Nebraska, we find a similar pattern to North Dakota's result both before 2009 and during the SURE program. 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 program changes as in North Dakota.

Iowa and Illinois: farmers are generally less responsive to preplant precipitation and its interaction with the SURE program. Relative to North Dakota and Nebraska, farmers are less responsive in corn acres in Iowa and Illinois, states in which both mean preplant precipitation and soil quality are much higher (table 3.2 and figure 3.4). Before 2009, the estimated coefficients on preplant 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 preplant precipitation conditions. In Illinois, the coefficient is statistically significant and indicates a small 0.1 percent decrease in acres given a 1 mm increase in preplant precipitation above the threshold. Though small, some adaptation is occurring in Illinois.

Three of four treatment effects are statistically significant under the SURE program, and three of four treatment effects are also significant in the post-SURE period. The SURE effect above the threshold in Iowa is similar in magnitude to that in North Dakota; a 1 mm increase in preplant precipitation increases corn acreage by 0.6 percent. After program termination in 2012, the decrease in the corn acreage function 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 characterizes much of the natural capital that underlies the production technology for agriculture in Illinois and Iowa. Consequently, corn is not a marginal crop as a function of preplant precipitation in these two states.

3.5.2 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.[26] Table 3.3 reports regression results, and figure 3.5 graphs the piecewise linear functions. We learned that North Dakota farmers are responsive in corn acres: in the pre-2009 period, corn acres decrease as preplant 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 preplant precipitation in substituting for corn. In fact, 11 of 12 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 as a function of preplant precipitation above the thresholds.

Termination of the SURE program generated several statistically significant responses both above and below the precipitation thresholds. Above the thresholds, the acreage relationships for corn, grassland, and wheat returned toward the preprogram relationship. This was also the case for wheat below the threshold.

Overall, in response to preplant precipitation, farmers in North Dakota show adaptation through cropping pattern followed by moral hazard in cropping pattern under the SURE program.

3.5.3 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 statisti-

26. Note that the type of wheat grown in North Dakota is spring wheat, not winter wheat. Spring wheat is planted during the normal spring planting season, and thus its acreage may be influenced by preplant precipitation.

Table 3.3 **Land-use estimation results for North Dakota**

	Corn (1)	Soybeans (2)	Grassland (3)	Wheat (4)
Preplant precipitation below threshold	–0.010**	0.092***	0.001	–0.020***
	(0.004)	(0.031)	(0.002)	(0.004)
Preplant precipitation below threshold	–0.015	—	–0.001	–0.911***
× after 2008	(0.041)	—	(0.004)	(0.056)
Preplant precipitation below threshold	0.008	–0.084**	0.006	0.954***
× after 2011	(0.042)	(0.037)	(0.005)	(0.058)
Preplant precipitation above threshold	–0.006***	0.008***	0.013***	0.004**
	(0.002)	(0.001)	(0.002)	(0.002)
Preplant precipitation above threshold	0.009***	–0.005***	–0.018***	–0.008***
× after 2008	(0.002)	(0.002)	(0.003)	(0.002)
Preplant precipitation above threshold	–0.010***	–0.003	0.007**	0.004**
× after 2011	(0.003)	(0.002)	(0.003)	(0.002)
Preplant temperature	–0.389**	0.521**	–0.357***	0.542***
	(0.151)	(0.195)	(0.128)	(0.079)
Preplant temperature squared	–0.019***	0.025***	–0.003	0.017***
	(0.005)	(0.008)	(0.003)	(0.005)
Planting precipitation	–0.004	–0.001	0.005*	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Planting precipitation squared	0.000	0.000	–0.000*	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	–0.047	0.014	–0.316***	–0.118
	(0.132)	(0.122)	(0.108)	(0.116)
Planting temperature squared	0.004	–0.019***	0.020***	0.006
	(0.007)	(0.005)	(0.003)	(0.005)
Crop-specific futures price	0.628***	–0.061	–0.219**	0.069
	(0.213)	(0.065)	(0.098)	(0.052)
Observations	352,963	352,963	352,963	352,963
R-squared	0.158	0.165	0.359	0.162
Number of PLSS sections	27,151	27,151	27,151	27,151
Threshold of preplant precipitation	100	65	125	85

Notes: Dependent variable in all regressions is the log of acres. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include section fixed effects, year fixed effects, and a quadratic time trend by state. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

cally significant but small responses to preplant precipitation as an adaptation strategy in Iowa, Illinois, and Nebraska (table 3.4). Nebraska and Illinois show similar patterns here of adapting to precipitation extremes by changing grassland acres. These effects are quite small, with estimated coefficients in the 0.001 to 0.003 range in absolute value.

Soybean acres show similarly small responses to preplant precipitation, with fewer estimated coefficients being statistically significant (table 3.5). Like corn, soybeans are not a marginal crop as a function of preplant pre-

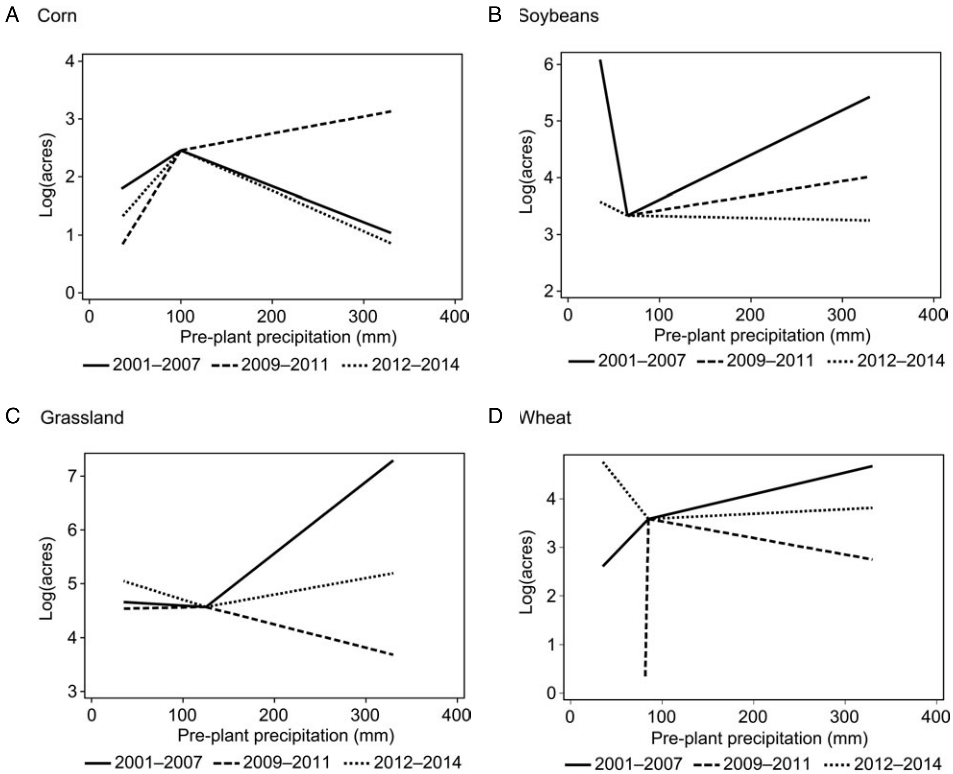

Fig. 3.5 Predicted effects of preplant precipitation on cropland acres in North Dakota (by policy regime)

Notes: The graphs display the predicted means of log(crop acres) in the sections as a function of preplant precipitation. Preplant precipitation is in millimeters.

cipitation in Iowa. However, soybeans are part of the cropping pattern response to the SURE program in both Iowa and Illinois. Farmers substitute away from soybeans below the thresholds in Iowa and Illinois and above the threshold in Iowa. Following the program's termination, farmers return to their preprogram 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.

3.6 Results II: Selection on Moral Hazard in Insurance Take-up

We use equation (2) to estimate insurance take-up regressions for two crops in two states: corn and soybeans in Illinois and Iowa.[27] In the piecewise linear

27. As mentioned earlier, insurance regressions are not estimated for crops in Nebraska and North Dakota due to issues in the county-level data that are not present in the section-level data.

Table 3.4 Land-use estimation results for grassland

	North Dakota (1)	Iowa (2)	Illinois (3)	Nebraska (4)
Preplant precipitation below threshold	0.001	–0.002*	0.002***	0.003*
	(0.002)	(0.001)	(0.000)	(0.001)
Preplant precipitation below threshold × after 2008	–0.001	0.005***	0.000	–0.004*
	(0.004)	(0.001)	(0.001)	(0.002)
Preplant precipitation below threshold × after 2011	0.006	0.002	–0.002**	0.004***
	(0.005)	(0.001)	(0.001)	(0.001)
Preplant precipitation above threshold	0.013***	–0.002***	0.001*	0.003***
	(0.002)	(0.000)	(0.000)	(0.000)
Preplant precipitation above threshold × after 2008	–0.018***	0.000	0.000	–0.002***
	(0.003)	(0.001)	(0.000)	(0.001)
Preplant precipitation above threshold × after 2011	0.007**	0.001***	–0.000	–0.001
	(0.003)	(0.000)	(0.001)	(0.001)
Preplant temperature	–0.357***	0.141***	–0.057	0.024
	(0.128)	(0.027)	(0.083)	(0.024)
Preplant temperature squared	–0.003	–0.005***	0.001	–0.000
	(0.003)	(0.001)	(0.003)	(0.004)
Planting precipitation	0.005*	0.000	–0.003***	–0.000
	(0.003)	(0.000)	(0.001)	(0.000)
Planting precipitation squared	–0.000*	0.000	0.000***	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	–0.316***	–0.458***	0.096	–0.095**
	(0.108)	(0.051)	(0.075)	(0.043)
Planting temperature squared	0.020***	0.010***	–0.005**	–0.004***
	(0.003)	(0.001)	(0.002)	(0.001)
Corn futures price	–0.219**	0.048***	–0.549***	0.096***
	(0.098)	(0.015)	(0.099)	(0.027)
Observations	352,963	650,260	589,836	173,112
R-squared	0.359	0.295	0.344	0.183
Number of PLSS sections	27,151	50,020	45,372	14,426
Threshold of preplant precipitation	125	170	435	140

Notes: Dependent variable in all regressions is the log of grassland acres. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include section fixed effects, year fixed effects, and a quadratic time trend by state. Regressions (1)–(4) use nonirrigated PLSS sections. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

regressions, the threshold values for preplant precipitation are taken from the land-use regressions for the respective crops and states. For example, the threshold of 370 mm from the corn acres regression in Iowa is applied as the threshold in the comparable insurance regression. Table 3.6 reports the results, and figure 3.6 graphs the results as a function of preplant precipitation.[28]

28. The estimated coefficients on the variables for futures prices for corn and soybeans lend credibility to the overall results on insurance take-up. These prices serve directly as parameters of revenue-based crop insurance. When insurance pays out, indemnity increases in futures price. The four estimates are positive and highly significant.

Table 3.5 **Land-use estimation results for soybeans**

	North Dakota (1)	Iowa (2)	Illinois (3)	Nebraska (4)
Preplant precipitation below threshold	0.092***	0.001	0.000*	–0.006***
	(0.031)	(0.001)	(0.000)	(0.001)
Preplant precipitation below threshold	–	–0.004***	–0.001*	0.005**
× after 2008	–	(0.001)	(0.000)	(0.002)
Preplant precipitation below threshold	–0.084**	–0.000	–0.000	0.000
× after 2011	(0.037)	(0.001)	(0.000)	(0.002)
Preplant precipitation above threshold	0.008***	0.001	–0.001***	–0.001
	(0.001)	(0.000)	(0.000)	(0.001)
Preplant precipitation above threshold	–0.005***	–0.002***	0.001**	0.002**
× after 2008	(0.002)	(0.000)	(0.000)	(0.001)
Preplant precipitation above threshold	–0.003	0.002***	–0.002***	0.001
× after 2011	(0.002)	(0.001)	(0.000)	(0.001)
Preplant temperature	0.521**	–0.004	–0.091***	–0.179***
	(0.195)	(0.019)	(0.035)	(0.035)
Preplant temperature squared	0.025***	–0.006***	–0.005***	–0.017***
	(0.008)	(0.001)	(0.002)	(0.005)
Planting precipitation	–0.001	–0.000	0.000	–0.003***
	(0.003)	(0.001)	(0.001)	(0.001)
Planting precipitation squared	0.000	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	0.014	0.088**	–0.127**	0.080
	(0.122)	(0.039)	(0.055)	(0.070)
Planting temperature squared	–0.019***	0.003***	0.009***	0.004*
	(0.005)	(0.001)	(0.002)	(0.002)
Soybeans futures price	–0.061	0.051**	0.070***	–0.014
	(0.065)	(0.025)	(0.016)	(0.015)
Observations	352,963	650,260	589,836	173,112
R-squared	0.165	0.073	0.083	0.079
Number of PLSS sections	27,151	50,020	45,372	14,426
Threshold of preplant precipitation	65	180	405	140

Notes: Dependent variable in all regressions is the log of soybean acres. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include section fixed effects, year fixed effects, and a quadratic time trend by state. Regressions (1)–(4) use nonirrigated PLSS sections. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

In studying selection on moral hazard, the question is whether SURE's treatment effect on crop insurance premiums per planted acre follows the sign and significance of the treatment effect on crop acres.[29] The results for corn provide reasonably strong supporting evidence. First, for corn acres in Iowa, the SURE treatment effect is negative and significant below the

29. We study land use and insurance take-up as concurrent decisions that reveal moral hazard and selection on moral hazard. In contrast, Einav et al. (2013) develop a two-period model with selection of insurance coverage in the first period and health-care utilization in the second period.

Table 3.6 **Estimation results for crop insurance take-up**

	Iowa		Illinois	
	Corn (1)	Soybeans (2)	Corn (3)	Soybeans (4)
Preplant precipitation below threshold	–0.000	0.000	–0.000	–0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Preplant precipitation below threshold × after 2008	–0.001**	–0.003***	0.001***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Preplant precipitation below threshold × after 2011	0.000	–0.001	–0.001*	–0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
Preplant precipitation above threshold	–0.007***	0.000**	–0.001***	–0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Preplant precipitation above threshold × after 2008	0.006***	0.001***	0.001***	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Preplant precipitation above threshold × after 2011	–0.008***	–0.000	0.002***	0.001**
	(0.003)	(0.000)	(0.001)	(0.000)
Preplant temperature	–0.038**	–0.101***	0.014	–0.060*
	(0.015)	(0.018)	(0.035)	(0.032)
Preplant temperature squared	–0.004***	–0.005***	–0.005***	–0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Planting precipitation	0.001***	0.001***	0.001*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Planting precipitation squared	–0.000**	–0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	–0.008	0.032	0.150***	0.161***
	(0.026)	(0.024)	(0.038)	(0.054)
Planting temperature squared	0.001	–0.001	–0.004***	–0.003**
	(0.001)	(0.001)	(0.001)	(0.002)
Corn/soybeans futures price	0.334***	0.201***	0.129***	0.115***
	(0.030)	(0.015)	(0.026)	(0.012)
Observations	1,287	1,287	1,285	1,291
R-squared	0.956	0.966	0.915	0.936
Number of counties	99	99	102	102
Threshold of preplant precipitation	370	180	395	405

Notes: Dependent variable in all regressions is the log of crop insurance premiums per planted acre. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include county fixed effects, year fixed effects, and a quadratic time trend by state. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

threshold; and positive and significant above the threshold (table 3.2). Corn insurance premiums follow the same pattern of treatment effects: negative and significant below; and positive and significant above (table 3.6). In addition, the magnitudes of the estimated coefficients are quite similar across the two regressions. Second, for corn acres in Illinois, the treatment effect is positive and significant below the threshold; and positive but insignificant above the threshold (table 3.2). Corn insurance premiums show roughly the same pattern: the treatment effects are positive and statistically significant

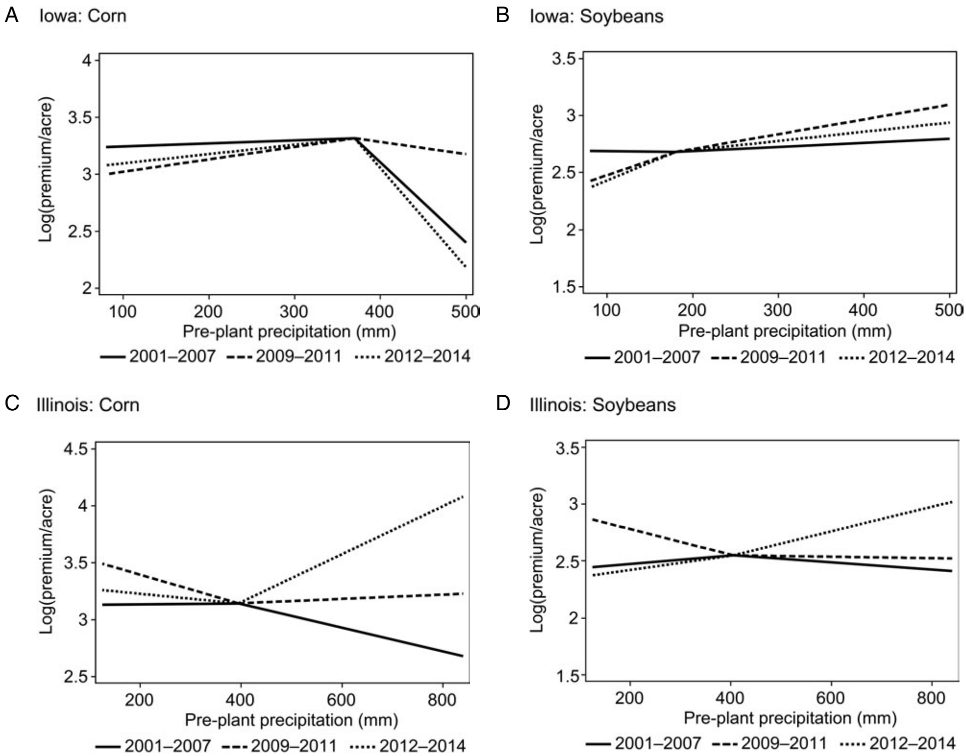

Fig. 3.6 Predicted effects of preplant precipitation on crop insurance premiums (by policy regime)

Notes: The graphs display the predicted means of log(premium/acre) in the counties as a function of preplant precipitation. Preplant precipitation is in millimeters.

both below and above the threshold. Moreover, the magnitudes of the estimated coefficients are quite similar across these two regressions.

The results for soybeans provide mixed evidence, with supporting evidence in each state on one side, but not both sides, of the respective thresholds. First, for soybeans acres in Iowa, the SURE treatment effect is negative and significant both below and above the threshold (table 3.5). Soybean insurance premiums follow the same pattern below the threshold, but they are positive and significant above the threshold (table 3.6). Second, for soybeans acres in Illinois, the treatment effect is negative and significant below the threshold; and positive and significant above the threshold. The treatment effects for soybean insurance premiums, in contrast, are positive and significant below the threshold and insignificant above the threshold.

We conclude, overall, that the results show limited evidence of selection on moral hazard. The county-level data on insurance premiums and weather may be a limiting factor in producing results that accord more closely to the soybean acreage results generated with section-level data.

Table 3.7 **Robustness checks for corn across states**

	North Dakota			Iowa		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Preplant precipitation below threshold	–0.010**	–0.009**	–0.010**	–0.000	0.000*	–0.000
	(0.004)	(0.003)	(0.004)	(0.000)	(0.000)	(0.000)
Preplant precipitation below threshold × after 2008	–0.015	–0.016	–0.011	–0.001**	–0.001***	–0.001**
	(0.041)	(0.040)	(0.039)	(0.000)	(0.000)	(0.000)
Preplant precipitation below threshold × after 2011	0.008	0.008	0.004	0.000	0.000	0.000
	(0.042)	(0.042)	(0.040)	(0.000)	(0.000)	(0.000)
Preplant precipitation above threshold	–0.006***	–0.006***	–0.005	–0.001	0.000	–0.001
	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)	(0.003)
Preplant precipitation above threshold × after 2008	0.009***	0.009***	0.008***	0.006**	0.004***	0.006*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)
Preplant precipitation above threshold × after 2011	–0.010***	–0.010***	–0.010***	–0.010***	–0.009***	–0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Preplant temperature	–0.388**	–0.415***	–0.414***	–0.068***	–0.058**	–0.103***
	(0.152)	(0.139)	(0.140)	(0.023)	(0.023)	(0.030)
Preplant temperature squared	–0.019***	–0.020***	–0.015**	–0.004**	–0.002	–0.004**
	(0.005)	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)
Planting precipitation	–0.004	–0.003	–0.006*	0.001	0.000	0.000
	(0.003)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)
Planting precipitation squared	0.000	0.000	0.000	–0.000*	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	–0.049	–0.048	–0.011	0.171***	0.125***	0.194***
	(0.133)	(0.126)	(0.131)	(0.035)	(0.030)	(0.036)
Planting temperature squared	0.004	0.004	0.003	–0.006***	–0.004***	–0.006***
	(0.007)	(0.007)	(0.007)	(0.001)	(0.001)	(0.001)
Corn futures price	0.628***	–0.236	0.330	0.192***	0.018	0.104***
	(0.213)	(0.172)	(0.209)	(0.034)	(0.026)	(0.035)
Observations	352,235	380,114	352,963	650,104	700,280	650,260
R-squared	0.158	0.147	0.159	0.027	0.027	0.027
Number of PLSS sections	27,095	27,151	27,151	50,008	50,020	50,020
Threshold of preplant precipitation	100	100	100	370	370	370

(*continued*)

3.7 Robustness Checks

In this section, we explore the sensitivity of our land-use regression results to three different modeling choices.

Removing sections that have zero acres of a crop during the study period. The first robustness check examines whether the results change if observations are removed from the small number of sections that have zero acres of a crop during the entire study period. As shown in columns with (a) in table 3.7, the estimated effects of preplant precipitation on corn acreage under the different policy regimes are almost the same as our main results reported in table 3.2. This is not surprising because the shares of the sections

Table 3.7 (continued)

	Illinois			Nebraska		
	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
Preplant precipitation below threshold	–0.000	–0.000	–0.000	–0.009***	–0.007**	–0.009***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Preplant precipitation below threshold × after 2008	0.001***	0.001**	0.001	0.012***	0.010***	0.012***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Preplant precipitation below threshold × after 2011	–0.001**	–0.001*	–0.000	–0.006***	–0.005***	–0.006**
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Preplant precipitation above threshold	–0.001***	–0.001**	–0.000	–0.005***	–0.004***	–0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Preplant precipitation above threshold × after 2008	0.001	0.001*	0.001	0.004***	0.002***	0.004***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Preplant precipitation above threshold × after 2011	–0.001***	–0.001***	–0.001***	0.000	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Preplant temperature	0.014	0.014	0.051	–0.102*	–0.114**	–0.046
	(0.049)	(0.049)	(0.046)	(0.056)	(0.055)	(0.084)
Preplant temperature squared	0.001	0.001	0.004	–0.016**	–0.013*	–0.017**
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)
Planting precipitation	–0.000	0.000	–0.000	–0.004***	–0.004***	–0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Planting precipitation squared	0.000	–0.000	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Planting temperature	–0.001	0.031	0.009	0.017	0.098	–0.054
	(0.062)	(0.064)	(0.062)	(0.087)	(0.075)	(0.123)
Planting temperature squared	0.004**	0.003*	0.004**	0.002	–0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
Corn futures price	0.038	0.009	0.088***	0.157***	0.164**	0.232***
	(0.032)	(0.039)	(0.031)	(0.043)	(0.070)	(0.031)
Observations	588,068	635,208	589,836	172,056	187,538	173,112
R-squared	0.026	0.033	0.030	0.091	0.086	0.094
Number of PLSS sections	45,236	45,372	45,372	14,338	14,426	14,426
Threshold of preplant precipitation	395	395	395	135	135	135

Notes: Dependent variable in all regressions is the log of acres. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include section fixed effects, year fixed effects, and a quadratic time trend by state. Columns with (a) drop the sections having zero acres of the crops planted over our sample period. Columns with (b) include observations in 2008 as a control year. Columns with (c) include potential endogenous variables, including aggregated precipitation and average temperature in the prior growing season from April to September and the interaction term between preplant precipitation and temperature. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

with zero corn acres during the study period are very small in each of the four states. The same conclusion applies to the other crops in the four states.

Treating 2008 as a control year. The second robustness check examines whether the results are sensitive to inclusion of observations from 2008 as part of the preprogram period—that is, expanding the period from 2001 to

2008 rather than 2001 to 2007.[30] In columns with (b) in table 3.7, we observe that the estimated effects of preplant precipitation on corn acreage under the different policy regimes are similar to our main results reported in table 3.2. The same conclusion applies to the other crops in the four states.

Including potentially endogenous variables. The third robustness check examines potential endogenous variables that may be correlated with both preplant precipitation and cropping pattern decisions. These variables include an interaction term between preplant precipitation and preplant temperature, aggregated precipitation from April through September of the previous growing season, and average temperature during the same previous growing season. As reported in columns with (c) in table 3.7 for corn, the coefficients of our preplant 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 3.2. One minor exception is Illinois, where three estimated coefficients change from significant to insignificant, although they remain quite small in magnitude. For the other crops in the four states, the sign, magnitude, and significance are similar to the main results.

3.8 Conclusion

This chapter develops a cohesive analysis of adaptation, moral hazard, and selection on moral hazard in farmer decision-making in response to preplant precipitation. The focus on preplant precipitation as a natural experiment created an opportunity to study both cropping pattern and crop insurance as part of an intermediate-run production frame. Prior to the SURE program, we find considerable heterogeneity in adaptation in cropping pattern, with farmers in Nebraska and North Dakota much more responsive than farmers in Illinois and Iowa. Adaptation is a form of self-insurance in the lexicon of Ehrlich and Becker (1972), whereby the choice of cropping pattern reduces the size of a prospective loss without changing the probability of extreme precipitation outcomes (as an artifact of the natural experiment).

The SURE program's shock to insurance deductibles created an opportunity to study moral hazard in cropping pattern and selection on moral hazard in crop insurance coverage. With cropping pattern, the finding continues that farmers in Nebraska and North Dakota are more responsive than in Illinois and Iowa. Following the program's termination, farmers largely reverted to the preprogram cropping pattern, lending credibility to a causal

30. Alternatively, we could have included observations from 2008 as part of the treatment period (2009–2011), since the SURE program was enacted on May 22, 2008. We did not do this for two reasons. First, that date is appreciably after the normal planting time in this region. Second, the program was the most complex that USDA's Farm Service Agency had ever undertaken such that it took some time to educate farmers about the program (Shields 2010).

interpretation of the program's impact. With insurance expenditures, the analysis covers Illinois and Iowa, where farmers increase (decrease) the rate of expenditure on corn when they increase (decrease) corn acres. They do so to a lesser degree with soybeans. This demonstrates a complementarity between risk-taking in land use and insuring the risk in the crop insurance market. This complementarity constitutes a specific form of adverse selection in an insurance market. To our knowledge, ours is the first study of selection on moral hazard in an insurance market other than health insurance.

The use of high-resolution spatial data on land use and weather—with the PLSS section as the unit of analysis for land use—created new insight into the mechanisms of adaptation and moral hazard. Cropping pattern and agricultural land use have long been conjectured as an important mechanism of adaptation to weather risk and climate change, and here we provide strong empirical support for the conjecture. Further insight comes with the link to moral hazard as a hidden action: the relationship between cropping pattern and preplant precipitation is neither observed by the insurance agent nor recorded in the insurance contract. The spatial data translated this relationship from an unobservable to an observable one for the econometric analysis. Lastly, the hidden action on cropping pattern under the SURE program translates into hidden information in the crop insurance market. Insurance companies, unwittingly, may be insuring different risks than those represented by farms' historical crop yields.

Evidence about farmers' adaptation to weather risk is essential for understanding the impact of climate change—after all, climate change is a change in weather risk. Agriculture is of particular importance due to its related impacts on economic growth, migration, and human conflict.[31] Looking to the future, the major climate vulnerability for the Midwestern agricultural sector is the risk of excess precipitation (Andresen, Hilberg, and Kunkel 2012). Widespread flooding events already occur over much of the region, and excessive rainfall events occur during the summer. While regional climate projections for the end of the century come with substantial uncertainty, the projections include increased precipitation, increased extreme precipitation, and little change or even a small decrease in summer precipitation (Winkler, Arritt, and Pryor 2012). Research is needed to investigate the effect of both existing and future climate change on land-use change in the globally significant Midwest agricultural sector as well as in other major agricultural regions of the world.

A challenge for public policymakers is to design efficient risk-management policies in a setting of climate change. When designing policies to encourage efficient adaptation, it is important to account for perverse incentives

31. Related literature includes, for example, Dell et al. (2012) and Burke et al. (2015) on economic growth; Feng et al. (2010) and Hornbeck (2012) on migration; and Miguel et al. (2004) and Hsiang et al. (2013) on human conflict.

for risk-taking provided by government insurance programs. Although the SURE program ended in 2011, the Agricultural Act of 2014 reconstituted a similar program to cover shallow losses that are typically part of the insurance deductible. Again designed to supplement crop insurance, this program—the Agriculture Risk Coverage program—created incentives for risk-taking in crop choice and production. Research is needed on this new program following the approach developed here, as program payments in 2015 were quite large, $5.9 billion (USDA-FSA 2017). More generally, research is needed to understand the interrelationship among adaptation, moral hazard, and selection on moral hazard across the range of sectors linked directly to weather and climate change.

Appendix

In the appendix, we (i) provide additional detail on the data and variables in the analysis, (ii) analyze the residual variation in the section-level preplant precipitation variables after controlling for fixed effects, and (iii) report on the variables and output from the yield regressions for corn and soybeans.

Data

Section 3 of the main text provides the primary description of the data and variables. We provide supplemental details here.

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. We use a GIS data layer for the PLSS (ESRI 2015). The 1 × 1 mile section grid scale facilitates comparison of grids across years when the grid spacing of the cropland data changed from 56 m to 30 m in 2006. The grid scale also makes tractable the analysis of local precipitation impacts.

Land use. The CDL program provides raster-formatted geospatial data on crops planted and other nonagricultural types of land cover for the United States. Each grid corresponds to a specific crop or type of land cover. The CDL's land cover classifications include more than 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 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 section. 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 percent to 95 percent, 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.

Weather. The 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 from 1950 to 2014. We compute weather variables by starting at the cell level and then aggregating to either the section level or the county level. These weather data cells are intersected with the PLSS sections using the Python language for ArcGIS.

Soil quality. The soil-quality data provide a useful perspective on the intrinsic quality of cropland across the states of Illinois, Iowa, Nebraska, and North Dakota. We do not describe these data in the main text, as they are not used in the regressions (instead relying on section fixed effects to control for soil quality). Nevertheless, they help explain the greater diversity of cropping pattern in Nebraska and North Dakota relative to Illinois and Iowa.

The soil-quality data are from USDA's Soil Survey Geographic (SSURGO) database. This spatially high-resolution database provides 10 × 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.

Figure 3A.1 in the appendix to this chapter displays the distribution of weighted land capability for our sample in the four states. Overall, Illinois and Iowa have a large share of good quality and moderate quality soils and only a small amount of poor quality soils. North Dakota has a large share of moderate quality soils but no good quality soils with weighted land capability less than 2. Nebraska similarly does not have any good quality soils with weighted land capability less than 2, and it has a substantial amount of poor quality soils.

The summary statistics for weighted land capability at the section level are shown in table 3A.1.

These numbers reinforce the more detailed data in figure 3A.1. Illinois and Iowa have the highest quality soil for their cropland, followed closely by North Dakota. Nebraska's cropland has the poorest quality soil of these four states by a substantial margin.

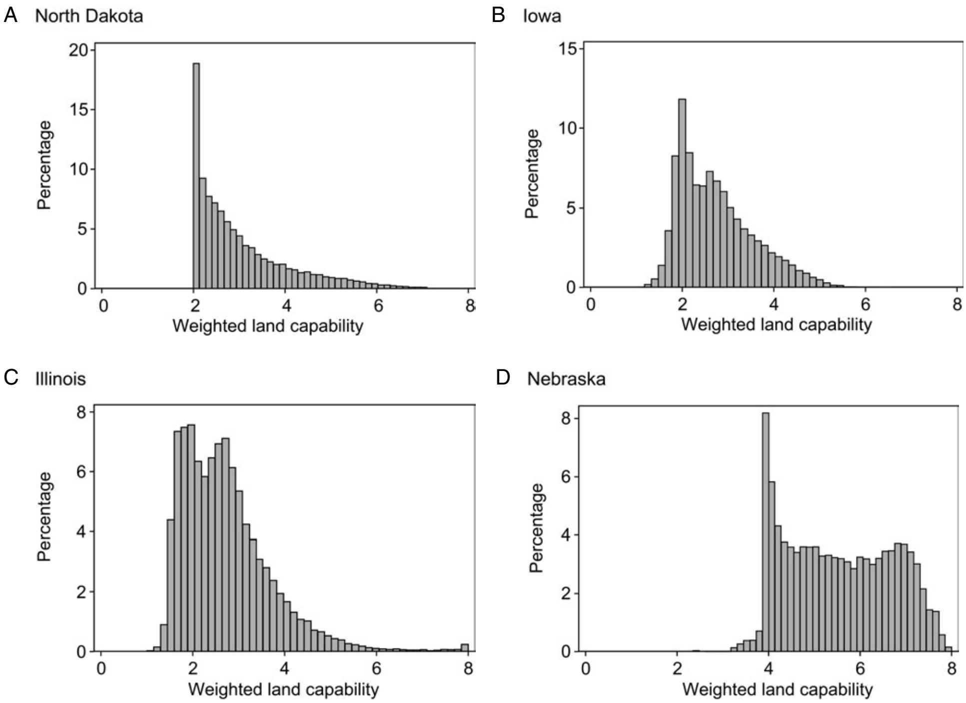

Figure 3A.1 Land capability class

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 rain-fed (nonirrigated) PLSS sections.

Table 3A.1 Summary statistics for weighted land capability by state

	Mean	Median	Std. dev.
Illinois	2.77	2.61	1.01
Iowa	2.74	2.59	0.83
Nebraska	5.52	5.45	1.15
North Dakota	3.03	2.68	1.05

Source: Authors' calculation.

Variation in Preplant Precipitation: Do Fixed Effects Absorb a Significant Amount of the Variation in the Section-Level Variables?

Our empirical approach relies on interannual variation in preplant precipitation after controlling for section and year fixed effects. A concern with this approach is that the fixed effects can absorb a significant amount of the variation in the precipitation variables. Following Fisher et al. (2012), we

Table 3A.2 **Variation of preplant precipitation under various sets of fixed effects**

		R^2 (1)	σ_e (2)	|e| > 10 mm (3)
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 section-level preplant precipitation on various sets of fixed effects (FE) to assess how much variation is absorbed by the FE. Column (1) reports the R^2s of the regressions. Column (2) reports the standard deviation of the residuals (remaining preplant precipitation variation) in millimeters. Column (3) reports the fraction of the observations having a residual larger than 10 mm.

explore how much of the variation is absorbed by the fixed effects. Table 3A.2 summarizes regressions of preplant 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 preplant 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, for example, the standard deviation of preplant 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 semiparametric approach. Of note, the same conclusion applies in the other three states—that is, the variation in the preplant precipitation variables remains substantial after accounting for fixed effects.

Yield Regressions: Summary Statistics and Output

Section 4 of the main text reports on the yield regressions for corn and soybeans. The purpose of the yield regressions is to establish that preplant precipitation affects crop yield, thus making preplant precipitation a valid factor in farmer decision-making. As reported in the main text, the regressions accomplish this purpose.

Since the yield regressions are only preliminary to the land-use and insurance take-up regressions, we report in the appendix on the summary statistics of the variables for the yield regressions (table 3A.3) and the regression results (table 3A.4). The data are county-level panel data from 2001 to

Table 3A.3 **Summary statistics of variables for yield regressions**

	Unit	Corn Mean	Corn Std. dev.	Soybeans Mean	Soybeans Std. dev.
Yield	bushels/acre	151.57	32.75	44.55	9.27
Preplant precipitation, accumulated	mm	287.36	131.73	286.38	131.64
Preplant temperature, daily average	°C	0.59	3.60	0.53	3.68
Planting-season precipitation, daily average	mm	3.57	1.35	3.85	1.38
Planting-season temperature, daily average	°C	13.70	2.03	17.41	2.35
June–August precipitation, monthly average	mm	102.38	36.30	102.11	36.30
June–August temperature, monthly average	°C	24.79	1.84	24.77	1.87
Maximum temperature in July, daily average	°C	29.52	2.31	29.50	2.34
Counties		229		229	
Observations		2,903		2,931	

Notes: Data represent three states: Illinois, Iowa, and the counties east of the 100th meridian in North Dakota. Yield variables are authors' calculations using data from National Agricultural Statistics Service. Weather variables are authors' calculations using data from Schlenker and Roberts (2009).

Table 3A.4 **Regression estimates of crop yield**

	Corn		Soybeans	
Preplant precipitation below threshold	0.0003***	(0.0001)	–0.0004***	(0.0001)
Preplant precipitation below threshold × after 2008	0.0001	(0.0002)	0.0008***	(0.0001)
Preplant precipitation below threshold × after 2011	–0.0004*	(0.0002)	–0.0004***	(0.0001)
Preplant precipitation above threshold	–0.0005***	(0.0001)	–0.0004***	(0.0001)
Preplant precipitation above threshold × after 2008	0.0006***	(0.0001)	0.0013***	(0.0002)
Preplant precipitation above threshold × after 2011	–0.0018***	(0.0003)	–0.0013***	(0.0002)
Preplant temperature	0.0858***	(0.0101)	0.0188***	(0.0067)
Planting-season precipitation	–0.0067**	(0.0028)	0.0004	(0.0024)
Planting-season temperature	–0.0011	(0.0084)	0.0082	(0.0075)
June–August precipitation	0.0049***	(0.0004)	0.0046***	(0.0003)
June–August precipitation, squared	–0.0000***	(0.0000)	–0.0000***	(0.0000)
June–August temperature	0.6237***	(0.0708)	0.5150***	(0.0512)
June–August temperature, squared	–0.0130***	(0.0014)	–0.0113***	(0.0010)
Maximum temperature in July	–0.1007***	(0.0084)	–0.0058	(0.0073)
Observations	2,903		2,931	
R-squared	0.741		0.712	
Number of counties	229		229	
Threshold of preplant precipitation	320		430	

Notes: Dependent variable in all regressions is the log of crop yield. Regressions estimated using piecewise linear functional form with the fixed effects estimator. Regressions include state-by-year fixed effects, county fixed effects, year fixed effects, and a quadratic time trend by state. Standard errors are clustered at the county level and shown in parentheses, and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

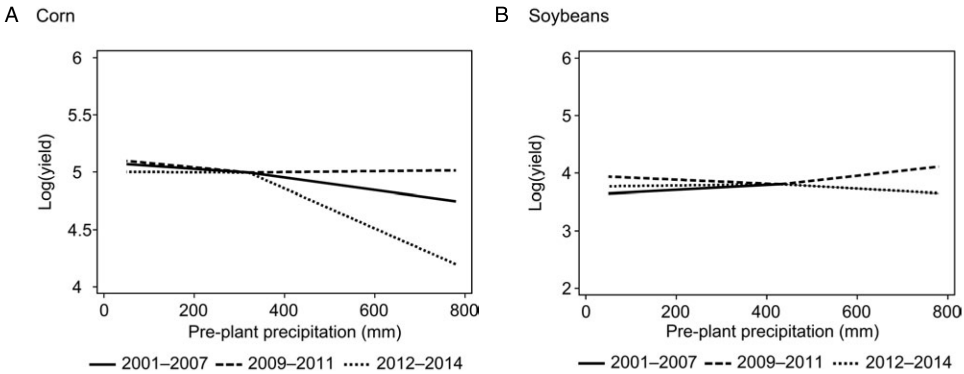

Figure 3A.2 Predicted effects of preplant precipitation on crop yield (by policy regime)

Notes: The graphs display the predicted means of log(yield) in the counties in the states of Illinois, Iowa, and North Dakota (east of the 100th meridian) as a function of preplant precipitation. Preplant precipitation is in millimeters.

2014 that are pooled for Illinois, Iowa, and eastern North Dakota. Corn yield has 2,903 observations, and soybean yield has 2,931 observations, both over 229 counties. The regressors are primarily weather variables. Precipitation and temperature variables are developed for each of the three phases of the crop production cycle: preplanting season, planting season, and growing season. In addition, a variable is developed for the daily average maximum temperature in July. These variables are guided, in part, by prior research on crop yield; Schlenker and Roberts (2009) study the effect of growing-season temperature on crop yield, and Urban et al. (2015) study the effect of extremely wet planting conditions on crop yield.

The main text reports on the results, which show small but (in most cases) statistically significant effects of preplant precipitation. The SURE treatment effects, in particular, are positive and significant in three of four cases (table 3A.4). These are contrary to expectations; in a separate work, we are investigating whether farmers planted corn and soybeans on land with higher-quality soils during the SURE program as a possible mechanism to explain these results. Figure 3A.2 graphs the piecewise linear functions for these two regressions.

The other weather variables, in large part, exert the expected effects on yield, as informed by the prior research (Schlenker and Roberts 2009; Urban et al. 2015). Planting-season precipitation has a significant, negative effect on corn yield. Both precipitation and temperature during the growing season (June–August) have positive, significant effects on corn yields and soybean yields. All four response functions are quadratic, with negative, small in absolute value, and significant estimated coefficients on the squared terms of the growing-season weather variables in both the corn and soybean regressions. High maximum temperatures in July have a negative effect on corn yield.

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